CROSS-LINGUAL VISION-LANGUAGE NAVIGATION

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ABSTRACT

Vision-Language Navigation (VLN) is the task where an agent is commanded to navigate in photo-realistic environments with natural language instructions. Previous research on VLN is primarily conducted on the Room-to-Room (R2R) dataset with only English instructions. The ultimate goal of VLN, however, is to serve people speaking arbitrary languages. To do this, we collect a cross-lingual R2R dataset, extending the original benchmark with corresponding Chinese instructions. But it is impractical to collect human-annotated instructions for every existing language. Based on the newly introduced dataset, we propose a general cross-lingual VLN framework to enable instruction-following navigation for different languages. We first explore the possibility of building a cross-lingual agent when no training data of the target language is available. The cross-lingual agent is equipped with a meta-learner to aggregate cross-lingual representations and with a visually grounded cross-lingual alignment module to align textual representations of different languages. Under the zero-shot learning scenario, our model shows competitive results even compared to a model trained with all target language instructions. Besides, we introduce an adversarial domain adaption loss to improve the transferring ability of our model when given a certain amount of target language data. Our dataset and methods demonstrate potentials of building scalable cross-lingual agents to serve speakers with different languages.

1 INTRODUCTION

Recently, the Vision-Language Navigation (VLN) task \cite{Anderson et al., 2018}, which requires the agent to follow natural language instructions and navigate in houses, has drawn significant attention. In contrast to some existing navigation tasks \cite{Mirowski et al., 2016, Zhu et al., 2017} where the agent has an explicit representation of the target to know if the goal has been reached or not, an agent in the VLN task can only infer the target from natural language instructions. Therefore, in addition to normal visual challenges in navigation tasks, language understanding and cross-modal alignment are essential to complete the VLN task.

However, existing benchmarks \cite{Anderson et al., 2018, Chen et al., 2019} for the VLN task are all monolingual in that they only contain English instructions. Specifically, the navigation agents are trained and tested with only English corpus and thus unable to serve non-English speakers. To fill this gap, one can collect the corresponding instructions in the language that the agent is expected to execute. But it is not scalable and practical as there are thousands of languages on this planet and collecting large-scale data for each language would be very expensive and time-consuming.

Therefore, in this paper, we study the task of cross-lingual VLN to endow an agent the ability to understand multiple languages. First, can we learn a model that is trained on existing English instructions but still able to perform reasonably well for a different language (e.g. Chinese)? This is indeed a zero-shot learning scenario where no training data of target language is available. An intuitive approach is to train the agent with English data, and at test time, use a machine translation system to translate the target language instructions to English, which are then fed into the agent for testing (see the above part of Figure 1). The inverse solution is also rational: we can translate all English instructions into the target language and train the agent on the translated data, so it can be

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directly tested with target language instructions (see the below part of Figure 1). The former agent is tested on translated instructions while the latter is trained on translated instructions. Both solutions suffer from translation errors and deviation from the corresponding human-annotated instructions. But meanwhile, the former is trained on human-annotated English instructions (which we view as “golden” data) and the latter is tested on “golden” target language instructions. Motivated by this fact, we design a cross-lingual VLN framework that learns to benefit from both solutions. As shown in Figure 1, we combine these two principles and introduce a meta-learner, which learns to produce beliefs for human-annotated instruction and its translation pair and dynamically fuse the cross-lingual representations for better navigation.

In this case, however, the training and inference are mismatched. During training, the agent takes source human language and target machine translation (MT) data as input, while during inference, it needs to navigate with target human instructions and source MT data. To better align the source and target languages, we propose a visually grounded cross-lingual alignment module to align the paired instructions via the same visual feature because they are describing the same demonstration path. The cross-lingual alignment loss can also implicitly alleviate the translation errors by aligning the human language and its MT pair in the latent visual space.

After obtaining an efficient zero-shot agent, we investigate the question that, given a certain amount of data for the target language, can we learn a better adaptation model to improve source-to-target knowledge transfer? The meta-learner and visually grounded cross-lingual alignment module provide a foundation for solving the circumstances that the agent has access to the source language and (partial) target language instructions for training. To further leverage the fact that the agent has access to the target language training data, we introduce an adversarial domain adaption loss to alleviate the domain shifting issue between human-annotated and MT data, thus enhancing the model’s transferring ability.

To validate our methods, we collect a cross-lingual VLN dataset (XL-R2R) by extending complementary Chinese instructions for the English instructions in the R2R dataset. Overall, our contributions are four-fold: (1) We collect the first cross-lingual VLN dataset to facilitate navigation models towards accomplishing instructions of various languages such as English and Chinese, and conduct analysis between English and Chinese corpus. (2) We introduce the task of cross-lingual vision-language navigation and propose a principled meta-learning method that dynamically utilizes the augmented MT data for zero-shot cross-lingual VLN. (3) We propose a visually grounded cross-lingual alignment module for better cross-lingual knowledge transfer. (4) We investigate how to transfer knowledge between human-annotated and MT data, and introduce an adversarial domain adaption loss to improve the navigation performance given a certain amount of human-annotated target language data.

2 Problem Formulation

The cross-lingual vision-language navigation task is defined as follows: we consider an embodied agent that learns to follow natural language instructions and navigate from a starting pose to a goal location in photo-realistic 3D indoor environments. Formally, given an environment $E$, an initial
Figure 2: XL-R2R dataset analysis. (a) Distribution of instruction lengths. (b) Distribution of sub-instructions per instruction. (c) and (d) are distributions of part-of-speech tags for Chinese and English instructions, respectively.

pose \( p_1 = (v_1, \phi_1, \theta_1) \) (spatial position, heading, elevation angles) and natural language instructions \( x_{1:N} \), the agent takes a sequence of actions \( a_t, x_{1:N} \) to finally reach the goal \( G \). Thus the VLN dataset \( D' \) is defined as \( \{(E, p_1, x_{1:N}, G)\}_{\epsilon=0%}^{\epsilon=100%} \). Note that we eliminate the footscript here for simplicity. At each time step \( t \), the agent at pose \( p_t \) receives a new observation \( I_t = E(p_t) \), which is a raw RGB image pictured by the mounted camera. Then it takes an action \( a_t \) and leads to a new pose \( p_{t+1} = (v_{t+1}, \phi_{t+1}, \theta_{t+1}) \). Taking actions sequentially, the agent stops when a \( \text{stop} \) action is taken.

A cross-lingual VLN agent learns to understand multiple languages and navigate to the goal. Without loss of generality, we consider a bilingual situation coined as cross-lingual VLN. For this specific task, we built the XL-VLN dataset \( D \), which extends the VLN dataset and includes a bilingual version of instructions. Specifically, \( D = \{(E, p_1, x_{1:N}^S, x_{1:N}^T, G)\}_{\epsilon=0%}^{\epsilon=100%} \), where \( S \) and \( T \) indicate source and target language domains separately. The source language domain \( S \) contains instructions in the source language covering the full VLN dataset \( D' \) (including training and testing splits), while the target language domain \( T \) consists of a fully annotated testing set and a training set in the target language that covers a varying percentage \( \epsilon \) of trajectories of the training set in \( D' \) (\( \epsilon \) may range from 0% to 100%). The agent is allowed to leverage both source and target language training sets and expected to perform navigation given an instruction from either the source or target language testing sets.

In this study, we first focus on a more challenging setting where no human-annotated target language data are available for training (\( \epsilon = 0\% \)), i.e., with no training data for the target language but the only access to the source language training set, the agent is required to follow a target language instruction \( x_{1:N}^T \) to navigate in houses. Then we investigate the agent’s transferring ability by gradually increasing the percentage of human-annotated target language instructions for training (\( \epsilon = 0\%, 10\%, ..., 100\% \)).

3 XL-R2R Dataset

We build a Cross-Lingual Room-to-Room (XL-R2R) dataset\(^1\) the first cross-lingual dataset for the vision-language navigation task. The XL-R2R dataset includes 4,675/340/783 trajectories for \( \text{train/validation seen/validation unseen} \) sets, preserving the same split as in the R2R dataset. Note that the official testing set of R2R is unavailable because the testing trajectories are held for challenge use. Each trajectory is described with 3 English and 3 Chinese instructions independently annotated by different workers.

**Data Collection.** We keep the English instructions of the R2R dataset and collect Chinese instructions via a public Chinese crowdsourcing platform. The Chinese instructions are annotated by native speakers through an interactive 3D WebGL environment, following guidance by Anderson et al.\(^2\). More details can be found in the Appendix.

**Data Analysis.** XL-R2R includes 5,798 trajectories in total and 17,394 instructions in both English and Chinese. In Figure\(^2\) we compare statistics of the English and Chinese corpora. Note that we segment Chinese words using the Jieba\(^3\) toolkit. Removing words with less than 5 frequency, we obtain an English vocabulary of 1,583 words and a Chinese one of 1,134 words. First, as shown

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\(^1\)XL-R2R is released at [https://github.com/zzxslp/Crosslingual-VLN](https://github.com/zzxslp/Crosslingual-VLN)

\(^2\)https://github.com/fxsjy/jieba

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in Figure 2a, Chinese instructions are shorter than English ones on average. Second, the instructions usually consist of several sub-instructions separated by punctuation, and we can observe that the numbers of sub-instructions per instruction distribute similar across languages (Figure 2b). Furthermore, Figure 2c and Figure 2d show that nouns and verbs, which often refer to landmarks and actions, are used more frequently in Chinese instructions (32.9% and 29.0%) than in English ones (24.3% and 13.7%).

4 Method

We present a general cross-lingual VLN framework in Figure 3. It is based on an encoder-decoder architecture and composed of three novel modules: a cross-lingual meta-learner (Meta), a visually grounded cross-lingual alignment module (txt2img), and an adversarial domain adaptation module. Particularly, as shown in Figure 3, both English and Chinese instructions are encoded by a shared encoder. Then the shared decoder takes the encoded contextual embeddings \( c_{L}^{1:N} \) from each language, the previous action \( a_{t-1} \), and the local visual feature \( I_{t} \) as input, and produces hidden states \( h_{e}^{t} \) for English and \( h_{zh}^{t} \) for Chinese. The meta-learner learns to assign probabilities to \( h_{e}^{t} \) and \( h_{zh}^{t} \), and then makes final predictions with the dynamically fused cross-lingual representation \( \tilde{h}_{t} \).

In addition, the txt2img module is introduced to align \( h_{e}^{t} \) and \( h_{zh}^{t} \) in the visual space with the visual feature \( I_{t} \) as an anchor point, improving the cross-lingual knowledge transfer via a visually grounded cross-lingual alignment loss. The adversarial domain adaptation module is particularly designed for the transfer setting where human-annotated target language instructions are also provided. We employ a domain discriminator that is trying to distinguish human-annotated instructions from machine translation (MT) instructions, and a gradient reversal layer to reverse the gradients back-propagated to the encoder so that the encoder is indeed trying to generate indistinguishable representations for both human-annotated and MT data and align the distributions of the two domains.

4.1 Cross-lingual Meta-Learner

We employ the sequence-to-sequence architecture in Anderson et al. (2018) for both languages. Receiving a pair of natural language instruction \( x_{L}^{1:N}, L \in \{S, T\} \), the agent encodes it with an embedding matrix followed by an LSTM encoder to obtain contextual word representations \( c_{L}^{1:N} \). The decoder LSTM takes the concatenation of current image feature \( I_{t} \) and previous action embedding \( a_{t-1} \) as input, and updates the hidden state \( s_{t-1} \) to \( s_{t} \) aware of the historical trajectory:

\[
s_{t} = \text{LSTM}_{\text{dec}}(s_{t-1}, [I_{t}, a_{t-1}])
\]

An attention mechanism is used to compute a weighted context representation, grounded on the instruction \( c_{L}^{1:N} \) by the hidden state \( s_{t} \), then obtain final hidden states \( h_{L}^{t} \) for each language:

\[
h_{L}^{t} = \tanh(W[\tilde{c}_{L}^{t}, s_{t}])
\]

The POS tags are obtained via Stanford Part-Of-Speech Tagger (Toutanova et al., 2003).
\[ c^C_t = \text{Attn}(c^C_{1:N}, s_t) \]  

To bridge the gap between source and target languages, we leverage a machine translation (MT) system to translate the source language in the training data into the target language. During testing, the MT system will translate the target language instruction into the source language. The MT data serves as augmented data for zero-shot or low-resource settings as well as associates two different human languages in general. So we take two instructions (the human language instruction and its MT pair) as input for both training and testing.

But we observed that the two instructions often generate different predictions, although one is the direct translation of the other. At each time step, when the agent observed the local visual environment, with two languages leading to different next positions, it remains a challenge which language representation to trust more.

Therefore, we propose a cross-lingual meta-learner that tries to help the agent make the judgment. At each time step, we let the cross-lingual meta-learner decide which language representation we should have more faith in, i.e., “learning to trust”. The meta-learner is a SoftMax layer which takes the concatenation of two hidden states \( h^S_t \) and \( h^T_t \) as input, and produces a probability \( \alpha_t \) representing the belief of the source language representation. The final hidden vector used for predicting actions is defined as a mixture of the representations in two languages:

\[ \hat{h}_t = \alpha_t h^S_t + (1 - \alpha_t) h^T_t \]  

Finally, the predicted action distribution for the next time step is computed as:

\[ P(a_t | a_{1:t-1}, I_{1:t}, x^S_{1:N}, x^T_{1:N}) = \text{softmax}(\hat{h}_t) \]  

### 4.2 Aligning Cross-lingual Representations through Visual Space (TXT2IMG)

The commonality of the input instructions is that they describe the same visual trajectory though in different languages. To better align two languages, we map \( h^S_t \) and \( h^T_t \) into the latent visual space and maximize their similarities with the shared visual representation. In other words, we utilize the shared visual representation as an anchor point in the visual space to align cross-lingual representations. Let \( I_t \) be the latent visual representation at time step \( t \) (e.g. the final layer of a ResNet), the loss function is formulated as:

\[ L_{T2T} = \sum_{t \in 1:T} (\| \psi(W^S I_t) - \psi(W^T h^S_t) \|^2 + \| \psi(W^T I_t) - \psi(W^T h^T_t) \|^2) \]

where \( \psi \) denotes a non-linearity activation such as ReLU or tanh, \( W^S, W^T \) are learnable projection matrices. L2 distance is used to measure the similarity between textual and visual representations in the same vector space. This txt2img module grounds the instructions into the visual space and ensures the consistency among cross-lingual representations and the visual inputs.

### 4.3 Transferring Knowledge via Adversarial Domain Adaptation

During training, we have human-annotated data for the source language and machine-translated data for the target language, while the agent is supposed to test on human-annotated instructions in target language. To bridge the gap between training and inference, we leverage an adversarial domain adaptation loss to make the textual representations indistinguishable across domains for the transfer setting, where a certain amount of human-annotated instructions for the target language is available during training.

A sentence vector \( \bar{x} \) is computed as the mean of the context vector \( c_{1:N} \) to a single vector, then forwarded to a domain discriminator through the gradient reversal layer. With the gradient reversal layer, the gradients minimizing domain classification errors are passed back with opposed sign to the language encoder, which adversarially encourages the encoder to be domain-agnostic. We then minimize the following domain adaptation loss:

\[ L_{\text{domain}} = -(y^H \log \hat{y}^H + (1 - y^H) \log(1 - \hat{y}^H)) \]

where \( y^H \) is the domain label of an instruction indicating whether it is from human annotation or machine translation, and \( \hat{y}^H \) is the approximation by the domain discriminator.
Table 1: Performance comparison for zero-shot setting. Reported results are averages of 5 individual runs. train w/ MT denotes the model trained with Chinese MT data. meta-learner is the framework presented in Figure 1 that aggregates two learning schemes with a cross-lingual meta-learner (Section 4.1). meta+txt2img equips the meta-learner with the txt2img module introduced in Section 4.2. The first three models are all for zero-shot learning. The last one, train w/ AN, is trained with 100% human-annotated Chinese data. All models are tested with human-annotated Chinese instructions.

5 Experiments

Evaluation metrics. The following evaluation metrics are reported: (1) Path length (PL), which measures the total length of predicted paths; (2) Navigation Error (NE), mean of the shortest path distance in meters between the agents final location and the goal location; (3) Success Rate (SR), the percentage of final positions less than 3m away from the goal location; (4) Oracle Success Rate (OSR), the success rate if the agent can stop at the closest point to the goal along its trajectory; (5) Success rate weighted by (normalized inverse) Path Length (SPL), which trades-off Success Rate against trajectory length; (6) Coverage weighted by Length Score (CLS) (Jain et al., 2019), which measures the fidelity to the described path and which is complementary to goal-oriented metrics.

5.1 Zero-shot Learning

We report results under the zero-shot setting in Table 1 to show the effectiveness of our two components, meta-learner and txt2img. First, the clear gap between train w/ MT and meta-learner proves that our meta-learner can successfully aggregate cross-representations of both human-annotated and MT data, which also indicates the insufficiency of solely using MT data for zero-shot learning. Second, the txt2img module further improves navigation efficiency (SPL) and instruction following fidelity (CLS), which validates the effectiveness of grounding and aligning cross-lingual representations via the visual space. Moreover, even though the agent does not have access to any annotated target language data, it achieves competitive results compared to train w/ AN that is trained with 100% annotated target language data.

5.2 Transfer Learning

Figure 4: We examine the influence of using different percentages (from 0% to 100%) of target language (Chinese) instructions to train agents. We enable adversarial domain adaption on top of meta+txt2img, and compare it with three baselines. AN: only partial Chinese annotations (0% to 100%) are used for training. AN+EN: partial Chinese annotations and 100% English annotations. AN+EN+MT: partial Chinese annotations, 100% English annotations, and 100% Chinese translations of those English instructions.
therefore we adopt Shared Enc-Dec, which has two separate encoder-decoder architectures; (2) \textit{Shared Enc}, which has a shared language encoder; (3) \textit{Shared Dec}, which has a shared policy decoder; (4) \textit{Shared Enc-Dec}, which shares both encoder and decoder, with different word embeddings for different languages. These models take English and Chinese instructions as input, for both training and testing. They are also compared with a monolingual model \textit{Base-mono}, which is a single encoder-decoder model trained and tested with Chinese instructions only.

Table 2 shows the results of the aforementioned models on validation seen and unseen sets. First, all cross-lingual models consistently perform better than the monolingual model (\textit{Base-mono}), remarking the usefulness of cross-lingual learning for improving navigation policy. Second, sharing parameters can further assist knowledge transfer and thus boost navigation performance. Furthermore, although \textit{Shared Enc} and \textit{Shared Enc-Dec} produce similar results, \textit{Shared Enc-Dec} is more efficient and more scalable since it yields a competitive good result with fewer parameters required, therefore we adopt \textit{Shared Enc-Dec} for other experiments.

5.4 Case Study

For a more intuitive understanding of the meta-learner, we visualize the confidences assigned to each language in Figure 6. In this case, the meta-learner trusts more in the human-annotated Chinese instruction which is of better quality. More specifically, at time step 10, when the meta-learner has the highest faith in the Chinese instruction, we visualize the textual attention on the whole instruction at this time step. Evidently, the corresponding textual attention on the Chinese command makes more sense than the machine-translated English command. The agent is supposed to keep turning
left and then move forward to the green plant. The attentions on Chinese instruction assigns 0.25 to “turn left”, and nearly zero attention to “head towards the door” which is already completed by previous actions. While the attention on English is more uniform and less accurate than on Chinese.

6 RELATED WORK

Vision and Language Grounding. Over the past years, deep learning approaches have boosted the performance of computer vision and natural language processing tasks (Krizhevsky et al., 2012; Sutskever et al., 2014; He et al., 2016; Vaswani et al., 2017). A large body of benchmarks are proposed to facilitate the research, including Image and Video caption (Lin et al., 2014; Krishna et al., 2017), VQA (Antol et al., 2015; Das et al., 2018), and visual dialog (Das et al., 2017). These tasks require grounding on both visual and textual modalities, but mostly limited to a fixed visual input. Thus, we focus on the task of vision-language navigation (VLN) (Anderson et al., 2018), where an agent needs to actively interact with the visual environment following language instructions.

Vision-Language Navigation. Several approaches have been proposed for the VLN task on the R2R dataset. For example, Wang et al. (2018) presented a planned-ahead module combining model-free and model-based reinforcement learning methods. Fried et al. (2018) introduced a speaker which can synthesize new instructions and implement pragmatic reasoning. Subsequent methods extend the speaker-follower model with Reinforced Cross-modal Matching (Wang et al., 2019a), self-monitoring (Ma et al., 2019), back-translation (Tan et al., 2019) etc. Previous works mainly improve navigation performance by data augmentation or leveraging efficient searching methods. In this paper, we address the task from a cross-lingual perspective, aiming at building an agent to execute instructions for different languages.

Cross-lingual Language Understanding. Learning cross-lingual representations is a crucial step to make natural language tasks scalable to all the world’s languages. Recently, cross-lingual studies on typical NLP tasks has achieved success, such as Part-of-Speech tagging (Zhang et al., 2016; Kim et al., 2017), sentiment classification (Zhou et al., 2016) and Named Entity Recognition (Pan et al., 2017; Ni et al., 2017). These studies successfully disentangle the linguistic knowledge into language-common and language-specific parts and learn both with individual modules. Moreover, cross-lingual image and video captioning (Miyazaki & Shimizu, 2016; Wang et al., 2019b) aim to bridge vision and language towards a deeper understanding, by learning a cross-lingual model grounded on visual inputs. Our dataset and method address the cross-lingual representation learning for the vision-language navigation task. To our knowledge, we are the first to study the cross-lingual learning in a dynamic visual environment, where the agent needs to interact with its surroundings and take a sequence of actions.

7 CONCLUSION

In this paper, we introduce a new task, namely cross-lingual vision-language navigation, to study cross-lingual representation learning situated in the navigation task where cross-modal interaction with the real world is involved. We collect a cross-lingual R2R dataset and conduct pivot studies towards solving this challenging but practical task. The proposed cross-lingual VLN framework is
proven effective in cross-lingual knowledge transfer. There are still lots of promising future directions for this task and dataset, e.g. to incorporate recent advances in VLN and greatly improve the model capacity. It would also be valuable to extend the cross-lingual setting to support numerous different languages in addition to English and Chinese.

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A P P E N D I X

A  I M P L E M E N T A T I O N  D E T A I L S

We follow the same preprocessing procedure as in previous work. A ResNet-152 pretrained on ImageNet is used to extract image features, which are 2,048-d vectors. Instructions are clipped with a maximum length of 80. Words are embedded into a 256-d vector space, and the action embedding is 32. The hidden size for the encoder and decoder LSTM is 512. The dropout ratio is 0.5. The meta-learner is a single fully connected layer. The dimension of vision-language alignment vector space is set to 1,024. Each episode consists of no more than 40 actions.

The network is optimized via the ADAM optimizer with an initial learning rate of 0.001, a weight decay of 0.0005, and a batch size of 100. The learning rate of domain adaptation loss is scheduled with an adaption factor (Ganin & Lempitsky, 2015):

\[ \lambda_p = \frac{2}{1 + \exp(-\gamma \cdot p)} - 1 \]  \hspace{1cm} (8)

where \( \gamma \) is set to 10 and \( p \) is learning steps. We use \( 0.2\lambda_p \) to train the domain discriminator.

We run each model 30,000 iterations and report the iteration with the highest SPL, and evaluate the models every 500 iterations.

B  R E S U L T S  O N  E N G L I S H  T E S T  S E T

For evaluating our proposed approach on the unseen test set, we participate in the Vision and Language Navigation challenge and submitted our results to the test server.

Here we treat Chinese as the source language and English as the target language. Hence for zero-shot learning, the agent has 100% Chinese annotated data but no English annotated data. The agent is commanded to follow English human instructions during testing. Results are shown in Table 3.

For zero-shot learning, our method (meta+txt2img) improves over the model trained with MT data only. For transfer learning, our method can efficiently transfer knowledge between Chinese and English data. The results are coherent with the reported results on the validation set. (See Table 1 and Figure 3).

| Test (unseen) | | | | |
|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| **Model** | **PL** | **NE ↓** | **OSR ↑** | **SR ↑** | **SPL ↑** | **Access to target training data** |
| train w/ mt | 12.40 | 8.12 | 0.325 | 0.224 | 0.172 | ✗ |
| meta+txt2img | 10.34 | 8.08 | 0.305 | 0.230 | 0.190 | ✗ |
| train w/ an | 10.92 | 7.47 | 0.344 | 0.259 | 0.212 | ✓ |
| transfer | 10.84 | 7.50 | 0.348 | 0.265 | 0.222 | ✓ |

Table 3: Performance comparison on the English test set. The first two rows are for zero-shot learning, the last two rows are trained with access to 100% target training data (i.e. English annotated instructions).

C  A B L A T I O N  S T U D I E S

**Meta-learner** To validate the effectiveness of the meta-learner, we compare it with a simple ensemble, which assigns equal confidence to two languages at all time steps, without any learnable parameters. The results are summarized in Table 4. Our meta-learner has higher performance on the validation unseen set, suggests that “learning to trust” is important for cross-lingual vision-language navigation.

**Adversarial Domain Adaptation Loss** To demonstrate the domain adaptation loss indeed enhance knowledge transfer between two languages, we compare it with our vanilla zero-shot model, a meta-learner equipped with a txt2img module. Table 5 shows that, as the size of target training data grows,
although the vanilla model can also benefit from the augmented data, the performance stops growing as the data size reaches 40% or 60%. Meanwhile, domain adaptation loss provides a more consistent and steady improvement. At the endpoint (100%), the SPL is 22.14 vs 21.50, proves its efficiency and the potential of transferring knowledge between different languages.

D COMPARING CHINESE ANNOTATED INSTRUCTIONS WITH MACHINE TRANSLATED ONES

We compare the statistics of the Chinese annotated dataset with a machine-translated one. The annotated instructions are more likely to contain fewer words as well as fewer instructions. Besides, nouns and verbs, which usually represent landmarks and actions in VLN task, are more frequent in annotated instructions than machine-translated ones.

![Figure 7](image_url)

Figure 7: Statistics of human annotated and machine translated data. (a) is instruction length distribution. (b) is sub-instruction number per instruction distribution. (c) is top 7 part-of-speech tag distribution of annotated and machine translated instructions.
E Chinese Data Collection Instructions

场景:

在标注中，你会看到如上图的场景。在场景中，你会看到许多圆柱。标记了你期望机器人前行的行进路线，其中红色圆柱表示最终的目的地，蓝色圆柱为轨迹的中间点，绿色表示起点（当前位置在起点故不可见）。请根据所给的路线用中文写下让机器人前进的路线的指令。

交互方式:
1. 左键单击并拖动可以观看全景，包括前后左右上下均可见；
2. 右键圆柱可以移动到圆柱所在的位置，并获得新的视野；

注意事项:
1. 机器人无法看到圆柱，请不要利用圆柱进行导航，圆柱仅为标注者提供路线参考；
2. 如果在图片中无法看到圆柱，请单击并拖拽查看全景图，寻找后续的轨迹；
3. 有时后目标在当前位置不可见时，例如在需要从一个房间到另一个房间时，可以通过指令移动到轨迹可见位置，如房间门口，再继续进行交互；
4. 你无法看见你所处位置的状态，即起点时无法见到绿色圆柱，终点则无法见到红色圆柱；
5. 在提供指令时，请使指令完整并反映出可供行走的轨迹的特征，切不要过于简单，如在上图中“到达门口”这类是不可取的；
6. 描述指令不必过分精确到圆柱，在其附近即可，只要大致展现出路径即可，即根据描述的指令能演出前进路线即可；
7. 鼓励使用家具的位置进行导航，如“经过右边的窗户”之类的；
8. 请注意指令的语法，指令从简，描述精确，如“略微右转”、“一直向前走”