A Follower-aware Speaker Model For Vision-and-Language Navigation

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Abstract

The speaker-follower models have proven to be effective in vision-and-language navigation, where a speaker model is used to synthesize new instructions to augment the training data for a follower navigation model. However, in previous work, the speaker model is follower-agnostic and fails to take the state of the follower into consideration. In this paper, we present a follower-aware speaker model that is constantly updated given the follower feedback, so that the generated instructions can be more suitable to the current learning state of the follower. Specifically, we optimize the speaker using a bi-level optimization framework and obtain its training signals by evaluating the follower on labeled data. Experimental results on the Room-to-Room and Room-across-Room datasets demonstrate that our methods can outperform strong baseline models across settings. Analyses also reveal that our generated instructions are of higher quality than the baselines.

1 Introduction

The task of vision-and-language navigation (VLN) requires an agent to navigate in a real-world environment given natural language instructions. In VLN, one of the major challenges is the lack of training data. To alleviate the issue, speaker-follower models (Fried et al., 2018) have been proposed. Specifically, in the speaker-follower models, an instruction-follower agent is trained to follow a provided natural language instruction and complete its specified goal, and a speaker model learns to model how humans describe routes and synthesize new instructions so as to create new training data for the follower.

While utilizing speaker-augmented data is widely adopted in VLN (Fried et al., 2018; Wang et al., 2019; Ma et al., 2019; Tan et al., 2019; Zhu et al., 2020; Hao et al., 2020; Wang et al., 2021; Chen et al., 2021), most of the previous methods focus on improving the follower navigation model. In contrast, how to improve the speaker model to generate data of higher quality is underexplored. In this line of research, Tan et al. (2019) propose to randomly add noise into the environments when generating instructions, so that the noisy environments can mimic unseen environments and the generated instructions can be more diverse; Liu et al. (2021) focus on better sampling the trajectories and propose a counterfactual path sampling method. They adversarially sample the most difficult paths for the follower and translate these paths into instructions using the speaker to perform data augmentation. In these methods, the speaker model is fixed when training the follower and fails to consider the current learning state of the follower.

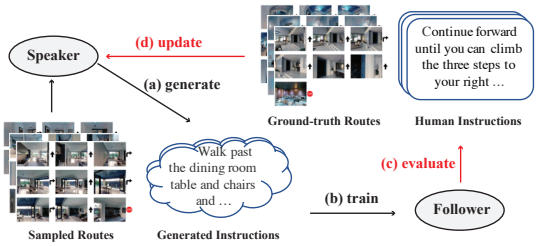

Figure 1: Previous work uses the speaker to generate instructions from sampled routes and train the follower. Our approach (in red) further obtains the feedback on labeled data and updates the speaker accordingly.

In this paper, we argue that the speaker model should be aware of the follower state so that the generated instructions can be more suitable for the follower. To this end, we frame the idea as a bi-level optimization problem and obtain the feedback signals to improve the speaker based on the follower performance on labeled data. As illustrated in Figure 1, the follower and speaker are trained in an iterative manner: after updating the follower for one step, it is evaluated on a batch of labeled data and the speaker is updated given the performance of the follower. In this way, the speaker is trained to directly optimize the performance of the follower.

Experiments on both Room-to-Room (Anderson et al., 2018b) and Room-across-Room (Ku

et al., 2020) demonstrate strong performance of our model over baselines across settings. Notably, our model without pre-training can achieve comparable performance with VLN-BERT (Majumdar et al., 2020), which is pre-trained with over millions of text sentences and image-text pairs. Analyses also reveal that our speaker can generate instructions of higher qualities than baselines.

2 Methods

We first briefly introduce the background:

Base Settings. VLN requires an agent to follow a given instruction and find a route in a photo-realistic environment (*e.g.* navigate in indoor living spaces). Formally, in an environment $\mathbf{e}$, the follower F parameterized by θ_F learns to model the distribution $P(\mathbf{r}|\mathbf{i};\theta_F)$, where $\mathbf{i}$ and $\mathbf{r}$ denote instruction and route variables, respectively.

The training data $\mathcal{D}$ consists of instruction-route pairs from different environments. Given a batch of instruction-route pairs $(\mathbf{i}_k, \mathbf{r}_k)$ from $\mathcal{D}$, we train the follower F to minimize the cross-entropy loss between its prediction $F(\mathbf{i}_k;\theta_F) = P(\mathbf{r}|\mathbf{i}_k;\theta_F)$ and the ground-truth label $\mathbf{r}_k$:

$$\min_{\theta_F} L_l(\theta_F) = \mathbb{E}_{(\mathbf{i}_k,\mathbf{r}_k)\sim\mathcal{D}}[\mathrm{CE}(\mathbf{r}_k, F(\mathbf{i}_k;\theta_F))]. \quad (1)$$

Speaker-Follower Models. Fried et al. (2018) propose to train a speaker model S parameterized by θ_S that models the distribution of $P(\mathbf{i}|\mathbf{r};\theta_S)$. As in Figure 1, with the speaker, we can perform back translation (Sennrich et al., 2016) on randomly sampled routes $\hat{\mathbf{r}}$ from the training environments $\mathcal{E}$ for data augmentation. Specifically, we first train the speaker S on the same training data as the follower. Then, given a batch of sampled route $\hat{\mathbf{r}}_k \sim \mathcal{E}$, we synthesize their human-like textual instructions $\hat{\mathbf{i}}_k = S(\hat{\mathbf{r}}_k;\theta_S)$. Afterwards, the synthesized training instances $(\hat{\mathbf{i}}_k, \hat{\mathbf{r}}_k)$ are used to update F:

$$\begin{aligned}\min_{\theta_F} L_u(\theta_F,\theta_S) &= \mathbb{E}_{(\hat{\mathbf{i}}_k,\hat{\mathbf{r}}_k)\sim\mathcal{E}}[\mathrm{CE}(\hat{\mathbf{r}}_k, F(\hat{\mathbf{i}}_k;\theta_F))] \\ &= \mathbb{E}_{\hat{\mathbf{r}}_k\sim\mathcal{E}}[\mathrm{CE}(\hat{\mathbf{r}}_k, F(S(\hat{\mathbf{r}}_k;\theta_S);\theta_F))].\end{aligned} \quad (2)$$

2.1 Optimizing the Speaker

As we can see from Equation 2, the resulting follower parameters θ_F^* depends on the speaker parameters θ_S, and we can express the dependency as $\theta_F^*(\theta_S)$. However, existing speaker-follower models fail to incorporate θ_S into the optimization process and θ_S is always fixed during training.

Formulation. In this paper, we propose to optimize the parameters of both the follower and speaker during back translation. Specifically, taking inspirations from Pham et al. (2021a,b), we optimize the speaker based on the performance of the follower on the labeled training data, which can be expressed as:

$$\begin{aligned}&\min_{\theta_S} L_l(\theta_F^*(\theta_S)), \\ &\text{where } \theta_F^*(\theta_S) = \operatorname*{argmin}_{\theta_F} L_u(\theta_F,\theta_S).\end{aligned} \quad (3)$$

The motivation of Equation 3 is that while the speaker-augmented data can provide additional supervisions for the follower, the main objective of the speaker is to make the follower better follow human instructions, thus we should focus on minimizing the loss on the labeled training data.

Approximation. Following previous work in bi-level optimization (Finn et al., 2017; Liu et al., 2018; Pham et al., 2021a,b), we can approximate argmin with one-step gradient update and alternatively update the parameters θ_F and θ_S.

Specifically, at training step t, we first sample a batch of routes and synthesize their instructions using the speaker S. The generated data is used to update the follower:

$$\theta_F^t = \theta_F^{t-1} - \eta_F \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1}), \quad (4)$$

where η_F is the learning rate.

Then, the speaker is updated to optimize the objective $L_l(\theta_F^t))$ with

$$\theta_S^t = \theta_S^{t-1} - \eta_S \nabla_{\theta_S} L_l(\theta_F^t)). \quad (5)$$

We can approximate the gradient $\nabla_{\theta_S} L_l(\theta_F^t))$ with (details in Appendix A)

$$-[\nabla_{\theta_F} L_l(\theta_F^t)^{\mathrm{T}} \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1})] \nabla_{\theta_S} \log P(\hat{\mathbf{i}}_k|\hat{\mathbf{r}}_k;\theta_S^{t-1}).$$

We can see that this equation resembles REINFORCE (Williams, 1992) in reinforcement learning. Therefore, this algorithm can also be interpreted as treating the similarity in the gradients of the follower model on the labeled data and on the speaker-augmented data as rewards, and update the speaker model using reinforcement learning.

End-to-End Reconstruction Loss. In this paper, we also propose to add a reconstruction loss for the speaker. Concretely, we compute the gradient of Equation 2 with respect to the speaker parameter θ_S using straight-through estimator, denoted as $\nabla_{\theta_S} L_u(\theta_F,\theta_S)$, and then update the speaker in an end-to-end manner. The final training loss is the

Model	Val-Seen			Val-Unseen			Test		
	SR↑	SPL↑	NE↓	SR↑	SPL↑	NE↓	SR↑	SPL↑	NE↓
Previous Work									
EnvDrop-ResNet (Tan et al., 2019)	62.1	59	3.99	52.2	48	5.22	51.5	47	-
AuxRN (Zhu et al., 2020)	70	**67**	3.33	55	50	4.71	55	51	5.15
RelGraph (Hong et al., 2020)	67	65	3.47	57	53	4.73	55	52	4.75
EnvDrop-CLIP-ResNet (Shen et al., 2021)	-	-	-	-	-	-	59.2	53	-
Our Implementations									
Base Follower-CLIP-ViT	60.5	56.6	3.97	54.9	49.3	4.81	-	-	-
EnvDrop-CLIP-ViT	66.1	61.7	3.61	59.2	52.4	4.31	60.0	53.9	4.38
Ours-CLIP-ViT	**70.8**	**66.6**	**3.25**	**61.6**	**55.1**	**4.18**	**62.2**	**56.2**	**4.09**

Table 1: Results on Room-to-Room. We report success rates (SR), success rates weighted by path length (SPL), navigation error (NE). The best scores are in **bold**.

Model	Val-Unseen-English				Val-Unseen-Hindi				Val-Unseen-Telugu				Test			
	SR↑	SPL↑	sDTW↑	nDTW↑	SR↑	SPL↑	sDTW↑	nDTW↑	SR↑	SPL↑	sDTW↑	nDTW↑	SR↑	SPL↑	sDTW↑	nDTW↑
Base	40.7	36.4	33.5	52.8	**46.8**	41.5	38.5	56.1	42.6	38.3	35.1	54.6	39.1	35.2	32.7	**49.7**
EnvDrop	42.4	38.3	35.5	53.9	46.5	41.5	38.5	56.0	44.4	39.3	36.5	**54.8**	**41.2**	**36.3**	**33.6**	48.8
Ours	**42.8**	**38.7**	**35.6**	**54.1**	46.7	**41.8**	**38.6**	**56.5**	**45.6**	**39.7**	**37.0**	54.4	**41.2**	36.2	**33.6**	49.3

Table 2: Results on Room-across-Room. We report success rates (SR), success rates weighted by path length (SPL), success rates weighted by dynamic time warping (sDTW), normalized dynamic time warping (nDTW). The best scores are in **bold**.

sum of Equation 5 and the reconstruction loss, and we will perform ablations on the two objectives in the experiment section.

3 Experiments

Datasets. We evaluate our models on the Room-to-Room (R2R) (Anderson et al., 2018b) and Room-across-Room (RxR) (Ku et al., 2020) datasets. The R2R dataset consists of 7,189 paths, and each path has 3 English instructions with an average length of 29. R2R is split into training, validation, and test sets. The validation set is split into *val-seen*, where paths are sampled from environments seen during training, and *val-unseen*, where paths are sampled from environments that are not seen during training. The paths in the test set are from new environments unseen in the training and validation sets. The RxR dataset follows the same environment division as R2R and there are 16,522 paths in total. The instructions have an average length of 78 and are in three languages, including English, Hindi, and Telugu.

Evaluation Metrics. Our primary metric is success rate (SR), and we also report navigation error (NE), success rate weighted by path length (SPL) on R2R. Following the suggestion in Ku et al. (2020), we also report normalized dynamic time warping (nDTW) and success rate weighted by dynamic time warping (sDTW) (Magalhães et al., 2019) on RxR.

Implementation Details. We build our model on top of EnvDrop (Tan et al., 2019), where the speaker and follower are based on LSTM (Hochreiter and Schmidhuber, 1997) and environmental dropout is used during back-translation. The follower is pre-trained with imitation and reinforcement learning. We follow Tan et al. (2019) to set the hyper-parameters, except that we use CLIP-ViT-224/16 (Radford et al., 2021) to extract vision features as CLIP vision encoders can be beneficial for VLN models (Shen et al., 2021).

3.1 Main Results

We report the main results in Table 1 and 2. We can see that our implementation of the baseline EnvDrop model is better than the previous work because of the stronger vision encoder we use. Based on the strong baseline, our model achieves further improvements on both validation and test sets, outperforming EnvDrop by 2.2% in the success rate on the R2R test dataset. However, the improvements are not as good on the RxR dataset, possibly because the instructions are much longer and thus it is hard to train a good speaker. Specifically, we find that the baseline speaker can only achieve a BLEU score of 7.4 on the English validation set, which

Follower	Speaker	Pre-exploration			Beam Search		
		Val-Seen	Val-Unseen	Test	Val-Seen	Val-Unseen	Test
EnvDrop	EnvDrop	66.9	64.2	-	74.9	68.4	-
Ours	EnvDrop	70.2	66.0	-	77.0	70.6	-
Ours	Ours	70.6	66.5	68.4	78.1	72.1	72.2

Table 3: Success rates of different configurations of the speaker-follower models in pre-exploration and beam search settings on Room-to-Room. The best configuration is using both *our* follower and *our* speaker models.

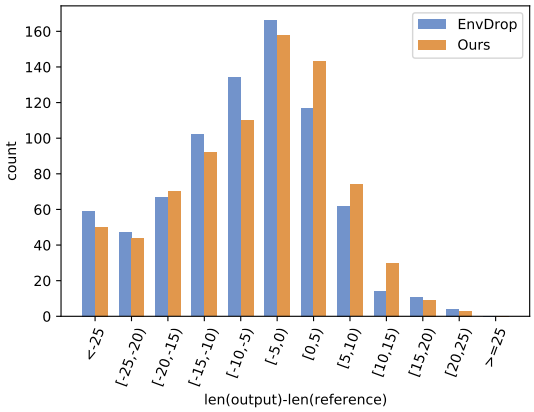

Figure 2: A histogram of the differences in length between the reference and model outputs. Baseline can often generate shorter instructions than the references, but our method can alleviate the issue.

leads to noisy augmented data and can impact the performance of speaker-follower models.

3.2 Analysis

In this section, we perform several analyses to gain insights towards our models.

Pre-exploration and Beam Search. We perform experiments in both pre-exploration and beam search settings following previous work (Tan et al., 2019). Because both the speaker and follower are used in the two settings, the evaluation results can reflect the quality of both of the models. As shown in Table 3, we find that the best configuration is using *our* follower and *our* speaker, suggesting that both our follower and speaker are more suitable for VLN than the baselines. Notably, in the beam search setting, our model without pre-training can achieve a success rate of 72.2%, which is comparable to the performance of VLN-BERT (Majumdar et al., 2020) that achieves a success rate of 73% and is pre-trained with over millions of text sentences and image-text pairs.

Generated Instructions. In Figure 2, we plot the histogram of length differences between the reference sentences and the generated instructions using *compare-mt* (Neubig et al., 2019). The figure suggests that the baseline model can often generate shorter instructions than the references, but our method can alleviate this issue, indicating that our methods can indeed improve the speaker quality during training. We also find that our generated instructions are quantitatively better than the baseline using automatic evaluations as in Appendix B.

Model	Val-Seen			Val-Unseen		
	SR	SPL	NE	SR	SPL	NE
Ours	70.8	66.6	3.25	61.6	55.1	4.18
-Recon.	68.9	63.5	3.33	60.2	53.1	4.30
-Bi-level	69.6	65.3	3.33	60.7	54.6	4.27

Table 4: Ablation studies on our proposed objectives. Our reconstruction loss and bi-level optimization loss are complementary to each other and ablating either one of them can lead to degraded performance.

Ablation Studies. As mentioned in Section 2.1, we perform ablation studies on both of our proposed objectives, namely the bi-level optimization loss (Equation 5) and reconstruction loss. As shown in Table 4, ablating either of the objectives can lead to degraded performance on the R2R validation sets, indicating that both the objectives can improve the model performance and they are complementary to each other.

4 Conclusions

In this paper, we propose to improve the speaker-follower model in vision-and-language navigation by constantly updating the speaker given the follower feedback during training. We frame the idea as a bi-level optimization problem and obtain the feedback signal based on the performance of the follower on labeled data. Experimental results on Room-to-Room and Room-across-Room datasets demonstrate that our method can outperform strong VLN baselines in different settings. Analyses also suggest that the quality of our speaker model is indeed improved during training. Future directions include testing our method on more datasets and investigating more options on the feedback signals.

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A Derivation of the Speaker Gradient

As shown in Section 2.1, at training step t, we update the follower according to:

$$\theta_F^t = \theta_F^{t-1} - \eta_F \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1}). \quad (6)$$

We define the *expected* parameters of the follower as $\bar{\theta}_F^t$:

$$\bar{\theta}_F^t = \mathbb{E}_{\hat{\mathbf{r}}_k \sim \mathcal{E}, \hat{\mathbf{i}}_k \sim P(\mathbf{i}|\hat{\mathbf{r}}_k; \theta_S^{t-1})}[\theta_F^{t-1} - \eta_F \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1})]. \quad (7)$$

Then, using the chain rule, we can obtain

$$\nabla_{\theta_S} L_l = \frac{\partial L_l}{\partial \bar{\theta}_F^t} \frac{\partial \bar{\theta}_F^t}{\partial \theta_S}, \quad (8)$$

where the first term can be approximated with $\frac{\partial L_l}{\partial \theta_F^t}$. Then, for the second term, we have

$$\frac{\partial \bar{\theta}_F^t}{\partial \theta_S} = \frac{\partial}{\partial \theta_S} \mathbb{E}_{\hat{\mathbf{r}}_k \sim \mathcal{E}, \hat{\mathbf{i}}_k \sim P(\mathbf{i}|\hat{\mathbf{r}}_k)}[\theta_F^{t-1} - \eta_F \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1})]. \quad (9)$$

We can assume that θ_F^{t-1} does not depend on θ_S with Markov assumption, and apply the REINFORCE (Williams, 1992) equation on the second term:

$$\begin{aligned} \frac{\partial \bar{\theta}_F^t}{\partial \theta_S} &= \frac{\partial}{\partial \theta_S} \mathbb{E}_{\hat{\mathbf{r}}_k \sim \mathcal{E}, \hat{\mathbf{i}}_k \sim P(\mathbf{i}|\hat{\mathbf{r}}_k)}[-\eta_F \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1})] \\ &= -\eta_F \mathbb{E}_{\hat{\mathbf{r}}_k \sim \mathcal{E}, \hat{\mathbf{i}}_k \sim P(\mathbf{i}|\hat{\mathbf{r}}_k)}[\nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1}) \frac{\partial}{\partial \theta_S} \log P(\hat{\mathbf{i}}_k|\hat{\mathbf{r}}_k; \theta_S^{t-1})], \end{aligned} \quad (10)$$

Using Monte Carlo approximation to approximate terms in Equation 10 using a batch of samples and substituting the result into Equation 8, we can get

$$\nabla_{\theta_S} L_l = -\eta_F [\nabla_{\theta_F} L_l(\theta_F^t)^{\mathrm{T}} \nabla_{\theta_F} L_u(\theta_F^{t-1}, \theta_S^{t-1})] \nabla_{\theta_S} \log P(\hat{\mathbf{i}}_k|\hat{\mathbf{r}}_k; \theta_S^{t-1}). \quad (11)$$

Note that here η_F is a hyper-parameter and can be incorporated into the learning rate of the speaker η_S, thus we remove this term in Section 2.1 and our derivation is complete.

B Automatic Evaluation of the Generated Instructions

As in Table 5, we measure the quality of the generated instructions in BLEU (Papineni et al., 2002) and BERTScore (Zhang et al., 2020). We find that our speaker can generate instructions of higher qualities according to the two metrics.

Model	Train	Val-Seen	Val-Unseen
BLEU			
EnvDrop	38.16	32.42	31.13
Ours	39.66	33.11	31.10
BERTScore			
EnvDrop	91.64	91.08	91.04
Ours	91.79	91.08	91.10

Table 5: Automatic evaluations of the generated instructions. The instructions generated by our model can obtain higher BLEU and BERTScore than the baseline.

C Related Work

We overview two lines of related work:

Vision-and-Language Navigation. Training embodied navigation agents has been an increasingly active research area (Anderson et al., 2018a,b; Chen et al., 2019; Ku et al., 2020; Shridhar et al., 2020; Padmakumar et al., 2022). Fried et al. (2018) propose to augment the training data with the speaker-follower models, which is improve by Tan et al. (2019) who add noise into the environments so that the speaker can generate more diverse instructions. Zhao et al. (2021) propose methods to measure the quality of the generated instructions and filter noisy samples. While using the speaker-augmented data has been widely used in VLN, most the of existing work has been focused on improving the follower navigation model. For example, the self-monitoring agent (Ma et al., 2019) improves cross-modal alignment through a visual-text co-grounding module and a progress monitor; Zhu et al. (2020) propose to utilize four self-supervised auxiliary tasks that can provide additional training signals for the agent. To our knowledge, how to improve the speaker model is often neglected in the current literature.

Bi-level Optimization. Bi-level optimization algorithms have been applied in various fields, such as learning initialization parameters (Finn et al., 2017), neural architecture search (Liu et al., 2018), re-weighting training data (Wang et al., 2020). Our method takes inspirations from (Pham et al., 2021a), which is applied in pseudo labeling and optimizes the teacher parameters given the student feedback. Similar techniques have also been used in machine translation (Pham et al., 2021b), where a meta-validation set is constructed to evaluate the model performance and provide feedback.

D Implementation Details

We build our model on top of EnvDrop (Tan et al., 2019) and follow their settings. Specifically, the speaker and follower are based on LSTM and environmental dropout is used during back-translation. We follow their hyper-parameter setting and we refer readers to their codebase[1] for details. The follower is pre-trained with imitation and reinforcement learning and the speaker is pre-trained with maximum likelihood training. We use CLIP-ViT-224/16 (Radford et al., 2021) to extract vision features. Each training takes about 3 days on 1 NVIDIA V100 GPU to finish. We report numbers of a single run for evaluations.

E License

We evaluate our models on the Room-to-Room (R2R) (Anderson et al., 2018b) and Room-across-Room (RxR) (Ku et al., 2020) datasets based on Matterport3D (Chang et al., 2017). The datasets are released under the Matterport3D Terms of Use.[2] The datasets do not contain any information that names or uniquely identifies individual people or offensive content. Our code is based on EnvDrop that is released under the MIT license.[3] We use the datasets and code for research purposes, which is consistent with their intended use.

F Limitations and Potential Risks

As in the experiments, our models may not work well when the instructions are long and it is hard to train a reasonable speaker model. Also, the datasets we use in the paper may make our model biased towards environments of American buildings.

[1] https://github.com/airsplay/R2R-EnvDrop

[2] http://dovahkiin.stanford.edu/matterport/public/MP_TOS.pdf

[3] https://github.com/airsplay/R2R-EnvDrop/blob/master/LICENSE