Generative Language-Grounded Policy in VLN with Bayes’ Rule

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ABSTRACT

Vision-and-language navigation (VLN) is a task in which an agent is embodied in a realistic 3D environment and follows an instruction to reach the goal node. While most of the previous studies have built and investigated a discriminative approach, we notice that there are in fact two possible approaches to building such a VLN agent: discriminative and generative. In this paper, we design and investigate a generative language-grounded policy which computes the distribution over all possible instructions given action and the transition history. In experiments, we show that the proposed generative approach outperforms the discriminative approach in the Room-2-Room (R2R) dataset, especially in the unseen environments. We further show that the combination of the generative and discriminative policies achieves close to the state-of-the-art results in the R2R dataset, demonstrating that the generative and discriminative policies capture the different aspects of VLN.

1 INTRODUCTION

Vision-and-language navigation (Anderson et al., 2018b) is a task in which a computational model follows an instruction and performs a sequence of actions to reach the final objective. An agent is embodied in a realistic 3D environment, such as that from the Matterport 3D Simulator Chang et al. (2017) and asked to follow an instruction. The agent observes the surrounding environment and moves around. This embodied agent receives a textual instruction to follow before execution. The success of this task is measured by how accurately and quickly the agent could reach the destination specified in the instruction. VLN is a sequential decision making problem: the embodied agent makes a decision each step considering the current observation, transition history and the initial instruction.

Previous studies address this problem of VLN by building a language grounded policy which computes a distribution over all possible actions given the current state and the language instruction. In this paper, we notice there are two ways to formulate the relationship between the action and instruction. First, the action is assumed to be generated from the instruction, similarly to most of the existing approaches (Anderson et al., 2018b; Ma et al., 2019; Wang et al., 2019; Hu et al., 2019; Huang et al., 2019). This is often called a follower model (Fried et al., 2018). We call it a discriminative approach analogous to logistic regression in binary classification.

On the other hand, the action may be assumed to generate the instruction. In this case, we build a neural network to compute the distribution over all possible instructions given an action and the transition history. With this neural network, we use Bayes’ rule to build a language-grounded policy. We call this generative approach, similarly to naïve Bayes in binary classification.

\textsuperscript{*}This work was done when the first author visited New York University.
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Walk between the tub and bathroom counter. Go through the opening next to the bathroom counter and into the little hallway. Wait next to the family picture hanging on the left wall.

Figure 1: The generative language-grounded policy for vision-and-language navigation.

Despite its similarity to the speaker model of Fried et al. (2018), there is a stark difference that the speaker model takes as input the entire sequence of actions and then predicts the entire instruction, which is not the case in ours. Instead, the generative language-grounded policy only considers what is available at each time step and chooses one of the potential actions to generate the instruction. We then apply Bayes’ rule and obtain the posterior distribution over actions given the instruction.

Given these discriminative and generative parameterization of the language-grounded policy, we hypothesize that the generative parameterization works better than discriminative parameterizations, because the former benefits from richer learning signal arising from generating the entire instruction rather than predicting a single action.

We empirically show that indeed the proposed generative approach outperforms the discriminative approach in the R2R dataset, especially in the unseen environments. Figure 1 illustrates the proposed generative approach on the R2R dataset. Furthermore, we show that the combination of the generative and discriminative policies results in near state-of-the art results in the R2R dataset, demonstrating that they capture two different aspects of VLN. We demonstrate that the proposed generative policy is more interpretable than the conventional discriminative policy, by introducing a token-level prediction entropy as a way to measure the influence of each token in the instruction on the policy’s decision.

2 BACKGROUND: VISION-AND-LANGUAGE NAVIGATION

In the R2R dataset (Anderson et al., 2018b), an agent moves on a graph that was constructed from one of the realistic 3D models of houses and buildings based on Matteport 3D dataset (Chang et al., 2017). At the beginning of each trial, the agent is given textual instruction, is placed at the start node and attempts to reach at the goal node by moving along the edges. At each node of the graph the agent observes the visual features of the surrounding environment and makes a decision to which neighbour node it will move next. When the agent determines that the current node is sufficiently close to the destination node, it outputs “STOP”, and the navigation trial ends. The agent is evaluated in terms of the accuracy of their final location and the trajectory length (Anderson et al., 2018b).

The difficulties in VLN mainly arise from the diversity of textual instructions. R2R provides multiple instructions for each trajectory. These instructions are created via crowd-sourcing, and their granularity and specificity highly vary (Li et al., 2019). The agent furthermore needs to generalize to unseen environments. Previous studies have reported that models with rich visual and textual features often overfit to the seen environments (Hu et al., 2019).

3 DISCRIMINATIVE AND GENERATIVE PARAMETERIZATIONS OF LANGUAGE-GROUNDED POLICY

Vision-and-language navigation (VLN) is a sequential decision making task, where an agent performs a series of actions based on the initially-given instruction, visual features, and past actions. Given the instruction $X$, past and current observations $s_t$ and past actions $a_{t-1}$, the agent computes the distribution $p(a_t | X, s_t, a_{t-1})$ at time $t$. For brevity, we write the current state that consists of the current and past scene observations, and past actions as $h_t = \{s_t, a_{t-1}\}$, and the next action prediction as $p(a_t | X, h_t)$. Figure 2 illustrates the relationship between these notations.
In VLN, the goal is to model $p(a_t| h_t, X)$ so as to maximize the success rate of reaching the goal while faithfully following the instruction $X$. In doing so, there are two approaches: *generative* and *discriminative*, analogous to solving binary classification with either logistic regression or naive Bayes.

In the *discriminative* approach, we build a neural network to directly estimate $p(a_t| h_t, X)$. This neural network takes as input the current state $h_t$ and the language instruction $X$ and outputs a distribution over the action set. Learning corresponds to

$$\max_{\theta} \sum_{n=1}^{N} \sum_{t=1}^{T_n} \log p(a_t^n| h_t^n, X^n),$$

where $N$ is the number of training trajectories.

In the *generative* approach, on the other hand, we first rewrite the action distribution as

$$p(a_t| h_t, X) = \frac{p(X| a_t, h_t)p(a_t| h_t)}{\sum_{a_t' \in \mathcal{A}} p(X| a_t', h_t)p(a_t'| h_t)}.$$  \hfill (2)

We assume $p'(a_t| h_t) = 1/|\mathcal{A}|$, where $\mathcal{A}$ is the action set. This assumption implies that the action is independent of the state without the language instruction, which is a reasonable assumption as the goal is specified using the instruction $X$. Under this assumption,

$$p(a_t| h_t, X) = \frac{p(X| a_t, h_t)}{\sum_{a_t' \in \mathcal{A}} p(X| a_t', h_t)}.$$  \hfill (3)

We then use a neural network to model $p(X| a_t, h_t)$. It takes as input a potential action $a_t$ and the hidden state $h_t$ and outputs the distribution over all possible instructions. Learning then becomes

$$\max_{\theta} \sum_{n=1}^{N} \sum_{t=1}^{T_n} \left( \log p(X^n| a_t^n, h_t^n) - \log \sum_{a_t' \in \mathcal{A}} p(X^n| a_t', h_t^n) \right).$$  \hfill (4)

Here $\log p(X^n| a_t^n, h_t^n)$ is a language model conditioned on the reference action $a_t$, while the second term $\log \sum_{a_t' \in \mathcal{A}} p(X^n| a_t', h_t^n)$ penalizes all the actions. Both terms of Eq. 4 are critical for learning the generative language-grounded policy. When we train the model only with the language model term $\log p(X^n| a_t^n, h_t^n)$ of Eq. 4, the resulting neural network does not necessarily learn how to distinguish different actions rather than simply to focus on generating the instruction from the state observation.

For navigation, we use the model to capture the probability of the instruction conditioned on each action $a_t \in \mathcal{A}$. The agent takes the action that maximizes the probability of generating the instruction:

$$\arg \max_{a_t} p(X| a_t, h_t).$$  \hfill (5)

This generative policy has a language model inside and navigates the environment by choosing an action that maximizes the probability of the entire instruction.

Later in the paper we empirically compare the discriminative and generative approaches, and show that the combination of the discriminative and generative approaches results in the best performance in the visual language navigation task.
4 RELATED WORK

While most of previous studies (Anderson et al., 2018b; Ma et al., 2019; Wang et al., 2019; Hu et al., 2019; Li et al., 2019; Hao et al., 2020) have relied on the discriminative approach \( p(a_t|X, h_t) \), a few of previous studies (Fried et al., 2018; Tan et al., 2019; Ke et al., 2019) have proposed the so-called speaker models which scores the instruction against the entire trajectory. Such speaker models are mainly used for two purposes; (i) data augmentation with automatically generated trajectories (Fried et al., 2018; Tan et al., 2019) and (ii) reranking the complete trajectories in beam decoding (Fried et al., 2018; Tan et al., 2019; Ke et al., 2019). They however have not been used for selecting local actions directly in either training or decoding. To the best of our knowledge, this paper is the first work that propose a generative language-grounded policy for vision-and-language-navigation.

Inspired by the the success of VLN, new experimental settings and navigation tasks in realistic 3D modeling have been proposed, such as expansions of the R2R dataset (Jain et al., 2019; Zhu et al., 2020) and dialog-based navigation tasks which include Vision-and-Dialog Navigation (Thomason et al., 2019), VLNA (Nguyen et al., 2019), and HANNA (Nguyen & Daumé III, 2019). Interactive visual question answering is also another interesting task variant (Gordon et al., 2018). The proposed generative language-grounded policy is widely applicable to these tasks where an agent solves a problem by following an instruction or having a conversation with another agent.

5 EXPERIMENTAL SETTINGS

5.1 R2R NAVIGATION TASK

We conduct our experiments on the R2R navigation task (Anderson et al., 2018b), which is widely used for evaluating language-grounded navigation models. R2R contains four splits of data: train, validation-seen, validation-unseen and test-unseen. From the 90 scenes of Matterport 3D modelings (Chang et al., 2017), 61 scenes are pooled together and used as seen environments in both the training and validation-seen sets. Among the remaining scenes, 11 scenes form the validation-unseen set and 18 scenes the test-unseen set. This setup tests the agent’s ability to navigate in unseen environments in the test phase. R2R has in total 21,567 instructions which are 29 words long on average. The training set has 14,025 instructions, while the validation-seen and validation-unseen datasets have 1,020 and 2,349 instructions respectively. Each trajectory in the R2R dataset has three or four instructions.

In our experiments, we use a single agent given a single instruction that navigates in an environment only once for each R2R navigation trial. We do not consider beam decoding, because we consider navigation with multiple agents unrealistic for the purpose of indoor, household navigation. We also disallow pre-exploring unseen environments. See Anderson et al. (2018a) for more discussion on the condition and evaluation of R2R navigation task.

5.2 NEURAL NETWORK MODELS

We use the network architectures of the speaker and follower models from (Fried et al., 2018) to implement our generative and discriminative models, respectively. We follow Fried et al. (2018) and create the embedding of the next action by concatenating the 4-dimensional orientation feature \([\sin \phi; \cos \phi; \sin \theta; \cos \theta]\) and the image feature extracted from a pretrained ResNet (He et al., 2016), where \(\phi\) and \(\theta\) are the heading and elevation angles, respectively. The generative policy scores an instruction based on the embedding of each of the next possible actions and the state representation which is also used by the discriminative policy. We emphasize that the proposed generative policy does not look ahead into the next state before taking the action.

5.3 TRAINING OF LANGUAGE-GROUNDED POLICIES

Both generative and discriminative policies are combined by

\[
\arg \max_{a_t} \left\{ \beta \log p(X|a_t, h_t) + (1 - \beta) \log p_f(a_t|X, h_t) \right\},
\]


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Table 1: Performance of generative policies and discriminative policies. +Aug. represents policies trained with the augmented dataset by Fried et al. (2018). Bold fonts are used for the best result as a single model in SR and SPL.

| Model                               | Validation (Seen) | Validation (Unseen) |
|-------------------------------------|-------------------|---------------------|
|                                     | TL↓ | NE↓ | SR↑ | SPL↑ | TL↓ | NE↓ | SR↑ | SPL↑ |
| Discriminative Policy               | 10.69 | 5.40 | 0.519 | 0.482 | 12.88 | 6.52 | 0.380 | 0.335 |
| Discriminative Policy +Aug. (A)     | 10.60 | 5.15 | 0.525 | 0.489 | 12.05 | 6.22 | 0.431 | 0.392 |
| Generative Policy                   | 11.23 | 5.53 | 0.481 | 0.451 | 12.98 | 6.17 | 0.434 | 0.371 |
| Generative Policy +Aug. (B)         | 11.45 | 4.78 | 0.563 | 0.531 | 13.92 | 4.78 | 0.476 | 0.405 |
| Generative+Discriminative Policy (A+B) | 10.18 | 4.67 | 0.568 | 0.540 | 12.06 | 5.42 | 0.489 | 0.437 |
| Generative+Discriminative Policy (A+B+BackTrack) | 11.30 | 4.58 | 0.575 | 0.541 | 14.65 | 5.19 | 0.518 | 0.439 |

Some of previous studies make use of augmented datasets (Fried et al., 2018; Ma et al., 2019; Tan et al., 2019; Ke et al., 2019). We use the same augmented dataset from Fried et al. (2018) which has been used by recent studies (Ma et al., 2019; Ke et al., 2019) for comparison. We use the validation-unseen dataset to select hyperparameters.

Following Fried et al. (2018), we first train a model with both the augmented and original training datasets. We then finetune it on the original training dataset alone. We use the same neural network architecture by Fried et al. (2018) with 512-units LSTM and the 300-d GloVe embeddings (Pennington et al., 2014). This network uses the panoramic view and action embeddings, following Fried et al. (2018). We use minibatch-size of 25. We use a single Nvidia V100 GPU to training.

We use the mixture of supervised learning and imitation learning (Tan et al., 2019; Li et al., 2019) for both the generative and discriminative policies, which are referred as teacher-forcing and student-forcing (Anderson et al., 2018b). In particular, during training between the reference action $a^T$ and a sampled action $a^S$, we select the next action by

$$a = \delta a^S + (1 - \delta)a^T$$

where $\delta \sim \text{Bernoulli}(\eta)$ following Li et al. (2019). We examine $\eta \in [0, 1/5, 1/3, 1/2, 1]$ using the validation set and choose $\eta = 1/3$.

FAST (Ke et al., 2019) is a framework of back-tracking to visited nodes. For single-agent back-tracking, FAST adapts a simple heuristic to continue navigation from one of the previously visited nodes. This back-tracking is triggered when the agent visits a node second time. Simple heuristic scoring of the sum of the transition logits is used to choose the returning node. We use this mechanism of back-tracking in the validation and test phase. We use the negative inverse of the logits to determine the node to continue from each time back-tracking is triggered. All movements in back-tracking are counted in the agent trajectory and penalized in the evaluation.

5.4 Evaluation Metrics

We use the following four metrics that are commonly used in VLN evaluation:

**Trajectory Length (TL)** is the length of the agent trajectory in meters.

**Navigation Error (NE)** is the shortest path distance in meters from the point the agent stops to the goal point.

**Success Rate (SR)** is the proportion of successes among all the trials. The task is successful when the agent stops within 3m from the goal point (Anderson et al., 2018b).

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1. The released augmentation dataset includes 178.3K trajectories with a single instruction for each.
2. For more details of training and evaluations, we closely follow the publicly available code: [https://github.com/ronghanghu/speaker_follower](https://github.com/ronghanghu/speaker_follower) of Fried et al. (2018).
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Table 2: Comparison of baselines and the proposed policy under single run experimental setting. Bold fonts for the first and second best results in SR and SPL.

**SPL** is short for Success weighted by (normalized inverse) Path Length introduced in [Anderson et al.](2018a). SPL is a variation of SR and is penalized by the trajectory length.

Among those evaluation metrics, we consider **SR** and **SPL** as primary ones because they are directly derived from the number of successes trials in R2R.

### 5.5 Baselines

We compare our approach against the following previous baselines. All of these, except for the random agent, follow the discriminative approach.

- **Random**: An agent that moves to one random direction for five steps ([Anderson et al.](2018b)).
- **Seq2Seq**: An LSTM-based sequence-to-sequence model ([Anderson et al.](2018b)).
- **RPA**: Combination of model-free and model-based reinforcement learning with a look-ahead module ([Wang et al.](2018)).
- **Follower**: An agent with panoramic view and trained with data augmentation ([Fried et al.](2018)).
- **Self-Monitoring**: An agent that integrates visual and textual matching trained with progress monitor regularizer ([Ma et al.](2019)).
- **RCM**: An agent that enforces cross-modal grounding of language and vision features ([Wang et al.](2019)).
- **EnvDrop**: An agent trained with combination of imitation learning and reinforcement learning after pretraining using environmental dropout and back translation for environmental data augmentation ([Tan et al.](2019)).
- **FAST**: An agent that exploits the fusion score of the local action selector and the progress monitor. This agent is able to back-track to visited nodes ([Ke et al.](2019)).
- **PRESS**: An agent with the pretrained language encoder of BERT and the capability to incorporate multiple introductions for one trajectory ([Li et al.](2019)). We compare our model against their model trained with a single instruction.

### 6 Results

#### 6.1 Generative vs. Discriminative Policies

Table 1 shows the performances of generative language-grounded policy (Generative Policy) and discriminative policy (Discriminative Policy). We show the result with and without data augmentation. All the policies were trained with stochastic sampling, resulting in better performance than those by [Fried et al.](2018) even with the discriminative baselines.

In the validation-seen dataset, the augmented generative policy achieves the better results than the discriminative counterpart, although it does not hold without augmentation. This suggests that generative policies require more data than discriminative policies do, while discriminative models easily
overfit to specific environments. In the validation-unseen dataset, the generative policy always performs better than the discriminative one in both SR and SPL.

We also notice that the combination of the generative and discriminative policy achieves the best result. The method of back-tracking further enhances the validation results especially in terms of SR. Since back-tracking requires extra transitions, the transitions length grows and the performance gain in SPL is smaller.

6.2 COMPARISON WITH BASELINES

Table 2 lists the performances in the validation-seen, validation-unseen and test-unseen datasets, collected from the public leaderboard and publications. We achieve near state-of-the-art result only with the original training dataset and augmented dataset released by Fried et al. (2018). In terms of SR, our model performs comparably to FAST which also uses the same neural network of Fried et al. (2018), while our model is better in SPL. In terms of SPL, our model is the second best only next to the EnvDrop model. However again our policy ends up with a better SR than EnvDrop does. Overall, the proposed approach is equivalent to or close to the existing state-of-the-art models in both SR and SPL.

The recently proposed PREV ALENT model (Hao et al., 2020) benefits from large scale cross-modal attention-based pretraining. They apply extensive data augmentation to create 6,482K image-text-action triples for pretraining, which is thus not included in the Table 2. As a result, they achieve SR of 0.54 and SPL of 0.51. On the other hand, we only use 178.3K augmented examples from Fried et al. (2018), widely used in previous studies (Ma et al., 2019; Ke et al., 2019). While such extensive data augmentation would likely boost our approach as well, we only use the released and widely shared augmented set for more direct comparison with previous studies. We nevertheless achieve the comparable SR with an order of magnitude smaller augmented data.

![Graphs showing precision and agreement rates for different policies and sets](image)

Figure 3: **Top:** the precision of actions by the generative (red) and discriminative (blue) models on the reference trajectory (dashed lines) and on navigation trajectories (solid lines). **Bottom:** the agreement of actions between the generative and discriminative models on shortest paths (dashed lines) and on navigation trials (solid lines). The horizontal axis corresponds to the time step of trials.

7 ANALYSES

7.1 GENERATIVE VS. DISCRIMINATIVE

Figure 3 plots the precision of predicted actions over time on the validation-seen and validation-unseen sets for both the generative policy and the discriminative language-ground policies. We

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Although our reported SPL is lower than 0.47 of the EnvDrop result, our SPL is 0.4647, only marginally lower.
use the Generative+Discriminative Policy (A+B) from Table 1 for this analysis. When the agents are presented with the gold trajectories, both policies predict actions more accurately than they would with their own trajectories. In real navigation, the action selection error accumulates, and prediction by both policies degrades over time. The generative policy, however, is more tolerant to such accumulated error than the discriminative policy is, achieving a higher precision in later steps. This is especially the case in unseen environments.

We present the agreement rate of action prediction between generative and discriminative policies at the bottom of Figure 3. The agreement drops over time, which implies that these policies behaves differently from each other, capturing different aspects of VLN.

7.2 Token-wise Prediction Entropy

The proposed generative policy allows us to easily inspect how it uses the instruction. A few tokens of instructions have often critical influence on the agent’s decision. For example, if an instruction ends with “...then stop at the kitchen” and the agent is between the kitchen and dinning room, the token “kitchen” decides where and when to “STOP”. Since the generative language-grounded policy relies on token-wise scoring of the original instruction with each action, we can examine the relationship between each action and specific tokens in the instruction.

We analyze how each token in the instruction affects the action prediction. The agent chooses the next action $a_t$ that maximizes $p(X|a_t, h_t)$ according to Eq. 4. An instruction is a sequence of tokens $X = \{w_0, \ldots, w_t, \ldots\}$. We introduce the token-wise prediction entropy (TENT) as

$$S(w_t) = - \sum_{a_t \in A} q(a_t, w_t) \log q(a_t, w_t), \quad (7)$$

where $q(a_t)$ is the probability of the action $a_t$ in the action set $A$:

$$q(a_t, w_t) = \frac{p(w_t|a_t, h_t, w_{t-1})}{\sum_{a_t \in A} p(w_t|a_t, h_t, w_{t-1})}. \quad (8)$$

TENT is easy to compute for generative language-grounded policy because it already computes $\log p(w_t|a_t, h_t, w_{t-1})$ for all possible actions $a_t$ during navigation. When some actions in $A$ are more influenced by a specific instruction token than the other actions, the entropy of those tokens are lower. Otherwise $S(w_t)$ is close to 1, which suggests that $p(w_t|a_t, h_t, w_{t-1})$ is almost same for any action, and that token $w_t$ is deemed less influential for the next action prediction.

We visualize how each token affects the agent decision with TENT in Figure 4. TENT always satisfies $0 \leq S(w_t) \leq 1$, and we use $1 - S(w_t)$ in visualization to illustrate positive peaks of the affects. We refer to $1 - S(w_t)$ as 1-TENT. If a token is highly influential to the action prediction, 1-TENT will be high.

Figure 4 visualizes how each action is related to each token in the instruction with two sample navigation instances from the validation-seen and validation-unseen datasets. We use Generative Policy +Aug. (B) from Table 1 without back-tracking. Both navigation trials end successfully within five and seven time steps, respectively. We draw the curves of 1-TENT for each time step.

In the early stage of the navigation, first few tokens exhibit large 1-TENT, which means the change of actions yields a great difference in their prediction. This tendency is observed widely in 1-TENT visualization for trials in both seen and unseen environments. We conjecture this is due to the lack of navigation history context. When the policy lacks the history, action predictions relies on the early part of the instruction.

In the seen navigation example, the agent is asked to navigate from the kitchen to the dinning room table. In the initial steps, the agent tries to go out from the kitchen, and phrases such as “right” and “walk out” have high 1-TENT. At $t = 3$, the agent is out of the kitchen and needs to turn left at the middle of the large room with high 1-TENT on “left” (see the reference panorama view). At last, the agent finds the dinning table and stops there with the high 1-TENT for tokens indicating the stop point.

In the unseen navigation instance, the agent is asked to navigate from the hallway, crosses the large bedroom and stops outside the carpet. The agent firstly moves toward the goal node based on the
Figure 4: Token-wise prediction entropy (TENT) for two navigation instances from validation-seen (top) and validation-unseen (bottom) datasets. Tokens of the instruction are aligned on the horizontal axis. The vertical axis corresponds to the 1-TENT drawn at each time step \( t \in \mathbb{N} \cup \{0\} \), as \( t + \frac{1}{\Delta}(1 - S(w_t)) \), where \( \Delta = 0.05 \) so that one vertical-tick corresponds to 0.05 in the scale of 1-TENT. We draw multiple lines that correspond to different time steps colored from blue to red and green. We attach the panoramic views for some of the trial time steps.

keywords “bedroom” and “fireplace”. It also exhibits high 1-TENT for “doorway”, which is a key to identifying the goal node to stop. This agent, however, passes the node of the success for the first time at \( t = 4 \). At \( t = 5 \), the agent has the high 1-TENT for both “doorway” and “rag” and then goes back to the same place with \( t = 4 \). Finally, it stops with the high 1-TENT for “before” and the slight 1-TENT for “rag” at \( t = 6 \). As we have seen here, the agent has different 1-TENT values depending on the context even if it is in the same place.

As we see here, token-wise entropy prediction and 1-TENT reflect why the agent takes a specific action by showing the variety of each token prediction in the reference instruction. 1-TENT is computed from \( \log p(w_t|a_t,h_t) \), which is directly used for the next action prediction. Although this 1-TENT analysis is similar to attention maps (Bahdanau et al., 2014; Vaswani et al., 2017), 1-TENT is much more directly related to the final prediction. The attention map represents the internal state of the neural network, while 1-TENT is computed based on the output of the neural network. This property makes the proposed 1-TENT a powerful tool for investigating and understanding the generative language-grounded policy.

7.3 Trajectory Fidelity

We analyze how well the trajectories followed by the proposed approach agree with the instructions using CLS (Jain et al., 2019), nDTW and SDTW (Ilharco et al., 2019). These three metrics are defined as:

CLS Coverage weighted by Length Score is the product of the path coverage of the reference trajectory and the length score which penalize the longer or shorter trajectory length than the reference trajectory length.

nDTW Normalized Dynamic Time Warping computes the fidelity of the trajectory given the reference path.

SDTW Success weighted by normalized Dynamic Time Warping is equal to nDTW for task success cases and otherwise 0.

These three metrics are based on the distance of the agent navigation trajectory from the reference trajectory. In the R2R dataset, each instruction is based on the shortest path (Anderson et al., 2018b). The trajectory paths are specified only in the instructions and therefore these metrics evaluate how
Table 3: CLS, nDTW and SDTW for generative policies and discriminative policies. Models are the same with described in Table 1. Bold fonts are used for the best result as a single model.

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8 **CONCLUSION**

We investigate two approaches, discriminative and generative, for the vision-and-language navigation task. We present the generative language-grounded policy which performs better than the more widely used discriminative approach. We combine the generative and discriminative policies to achieve the state-of-the-art results for the Room-2-Room navigation dataset in both SR and SPL metrics. Finally, we demonstrate the interpretability of the proposed generative language-grounded policy by designing the token-wise prediction entropy.

The proposed generative parameterization, including 1-TENT visualization, is directly applicable to language-grounded reinforcement learning, such as Zhong et al. (2020), Hermann et al. (2017), which should be investigated in the future. It is however important to also investigate an efficient way to approximate the posterior distribution in order to cope with a large action set, for instance, by importance sampling and amortized inference.

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