LEARNING COMPACT REWARD FOR IMAGE CAPTIONING

Nannan Li and Zhenzhong Chen∗
School of Remote Sensing and Information Engineering, Wuhan University

ABSTRACT

Adversarial learning has shown its advances in generating natural and diverse descriptions in image captioning. However, the learned reward of existing adversarial methods is vague and ill-defined due to the reward ambiguity problem. In this paper, we propose a refined Adversarial Inverse Reinforcement Learning (rAIRL) method to handle the reward ambiguity problem by disentangling reward for each word in a sentence, as well as achieve stable adversarial training by refining the loss function to shift the generator towards Nash equilibrium. In addition, we introduce a conditional term in the loss function to mitigate mode collapse and to increase the diversity of the generated descriptions. Our experiments on MS COCO and Flickr30K show that our method can learn compact reward for image captioning.

1 INTRODUCTION

Image captioning is a task of generating descriptions of a given image in natural language. In a general encoder-decoder structure (Vinyals et al., 2015), image features are encoded in a CNN and decoded into a caption in a word by word manner. Based on the loss function, typical approaches addressing the problem could be divided into three categories: MLE (Maximum Likelihood Estimation), RL (Reinforcement Learning) and GAN (Generative Adversarial Network).

Early proposed methods were based on MLE function and made improvements by designing specific model structure (Xu et al., 2015). MLE adopts the cross-entropy loss and learns a one-hot distribution for each word in the sentence. By maximizing the probability of the ground truth word whilst suppressing other reasonable vocabularies, the probability distribution learned by MLE tends to be sparse and the generated captions have limited diversity (Dai et al., 2017). On the other hand, RL has advantages in boosting the model performance by optimizing the handcrafted metrics (Rennie et al., 2017; Liu et al., 2017; Chen et al., 2019). However, due to the reward hacking problem, RL maximizes the reward in an unintended way and fails to produce human-like descriptions (Shetty et al., 2017; Fu et al., 2018). Considering naturalness and diversity of the generated captions, GAN has raised attention in image captioning for its capability of producing descriptions that are indistinguishable from human-written ones (Dai et al., 2017; Shetty et al., 2017; Chen et al., 2019). See Figure 1 for a few examples.

In image captioning, the generator of GAN learns true data distribution by maximizing the reward function learned from a discriminator, and the discriminator distinguishes the generated sample from the true data. The adversarial training converges to an equilibrium point (i.e., Nash equilibrium) at which both the generator and discriminator cannot improve (Goodfellow et al., 2014). GAN is less biased towards frequently occurring n-grams and learns to describe images with human-like descriptions (Shetty et al., 2017). However, previous work of adversarial networks in image captioning gives one reward function $D$ for a complete sentence consisting of $n$ words. This strategy causes the reward ambiguity problem (Ng et al., 1999) since which word(s) causes the reward to increase or decrease is not accounted for, and thus there are many optimal policies that determine the sentence can explain one reward. As shown in Figure 2, the generated two captions have the same reward (0.7) in GAN, whereas the contribution of each word to this reward remains unknown. The first caption gives the wrong verb “looking at” whilst the second caption has an incorrect object “a plate of food”. However, the ambiguous reward in GAN makes it unable to locate the inappropriate words. On the other hand, from the perspective on the system level, learning sentence-level reward from different image-caption pairs is analogous to learning reward of a trajectory from different system dynamics, which makes the discriminator unable to distinguish the true reward functions from those shaped by the environment dynamics (Fu et al., 2018).

Facing above challenges, we adopt Adversarial Inverse Reinforcement Learning (AIRL) (Fu et al., 2018) to solve the re-
ward ambiguity problem by learning a compact reward function, where compact means the reward function should satisfy two conditions: 1) The reward is word-wise and disentangled for each word in a sentence from different image-caption pairs, as shown in Figure 2. 2) The reward difference of two words is positively correlated to their semantic difference. For instance, words with similar semantics, such as children and kids, correspond to close reward values. A compact reward function can precisely tell the contribution of each word and thus help to locate the wrong words. It saves the effort of predefining a handcrafted reward function, and can recover the true reward up to a constant at optimality. Driven by such compact reward function from the discriminator, the generator can learn the optimal policy and thus produces qualitative descriptions. However, there are still two major problems to address: 1) AIRL is difficult to converge to Nash equilibrium using policy gradient, requiring Hessian of the gradient vector filed being positive definite (Mescheder and Geiger, 2017). We will discuss this in detail in Section 4.2. 2) As a GAN based method, AIRL has a sharp decision boundary for two disjoint distributions, which means the discriminator can be far more stronger than the generator. The consequence is a limited diversity in the generated captions, which is a commonly encountered issue in GAN called mode collapse (Mirza and Osindero, 2014).

In this paper, we propose a refined AIRL method to learn a compact reward function for each word, as well as achieve stable adversarial training by refining the loss function to shift the generator towards Nash equilibrium. In addition, a conditional term is introduced in the loss function to mitigate mode collapse and to increase the diversity of the generated descriptions. Both the caption evaluator (i.e., discriminator) (Cui et al., 2018; Sharif et al., 2018) and the generator are cast into this unified framework, where the discriminator evaluates captions using a learned compact reward function, and the generator produces qualitative image descriptions. We demonstrate the effectiveness of our method in the experiments.

3 Adversarial Inverse Reinforcement Learning

Due to the high variance estimate of a full sentence and the reward ambiguity problem, instead of learning reward for a complete sentence, we could learn the reward distribution \( p_\theta(w_t, s_t) \) at time \( t \) for each word-state pair \( (w_t, s_t) \) so that the true reward function can be recovered at optimality (Fu et al., 2018). In the following, we use \( w_t \) to represent the word at time \( t \), and \( s_t \) is the corresponding state vector at time \( t \). Note that in an LSTM based model structure, \( s_t \) refers to the hidden state of the LSTM cell. In the following, we introduce how AIRL disentangles reward for each word-state pair \( (w_t, s_t) \).

AIRL is an adversarial reward learning algorithm based on Maximum-Entropy-IRL. Finn et al. (2016) first proved that Maximum-Entropy-IRL is mathematically equivalent to GAN under a special form of the discriminator:

\[
D_\phi(w_t, s_t) = \frac{p_\theta(w_t, s_t)}{p_\theta(w_t, s_t) + \pi_\psi(t)} \tag{1}
\]

where \( p_\theta(w_t, s_t) \) is the data distribution estimated by the discriminator at time \( t \), parameterized by \( \theta \). \( p_\theta(w_t, s_t) \) is estimated using the natural exponential function \( p_\theta(w_t, s_t) = \exp \{f_\theta(w_t, s_t)\} \), where \( f_\theta(w_t, s_t) \) is the reward function. \( \pi_\psi(t) \) is the policy distribution produced by the generator at time \( t \), parameterized by \( \psi \). \( \pi_\psi(t) \) is the generated vocabulary distribution under the context of image captioning. \( D \) is the decision boundary, which represents the probability that \( (w_t, s_t) \) comes from the true word distribution rather than \( \pi_\psi \). The discriminator is trained to differentiate between the true words and the generated words whereas the generator tries to fool the discriminator by learning a policy \( \pi_\psi \) to maximize the reward \( f_\theta \) from \( D \).

Considering the reward ambiguity problem, Fu et al. (2018) further extended the above theory to AIRL by introducing a reward shaping term \( h_\psi \) into \( f_\theta(w_t, s_t) \). The reward shaping term disentangles reward from different system dynamics, which refer to different image-caption pairs under the context of image captioning.

\[
f_{\theta\psi}(w_t, s_t) = g_\theta(w_t, s_t; s_{t+1}) + \gamma h_\psi(s_{t+1}) - h_\psi(s_t) \tag{2}
\]

where \( g_\theta \) denotes the reward approximator that recovers the true reward up to a constant, and \( h_\psi \) is the reward shaping term that
Algorith 1: refined AIRL

Initialize the vocabulary distribution $\pi_\phi$ and discriminator $f_{\theta, \phi}$.

for iteration $i$ in $\{1, ..., N\}$ do

Obtain caption $\{w_1^{\text{true}}, ..., w_n^{\text{true}}\}$ from the ground truth.

Collect generated caption $\{w_1, ..., w_n\}$ using the vocabulary distribution $\pi_\phi(t)$.

$D_{\theta, \phi} \leftarrow \text{sigmoid}(f_{\theta, \phi} - \log(\pi_\phi(t)))$

Update $(\theta, \phi)$ via Eq. (6) for the discriminator.

Update $\psi$ via Eq. (12) for the generator.

end

preserves the optimal $\pi_\phi$. $\gamma$ is a constant in range $(0, 1]$. Then the estimated data distribution becomes

$$p_{\theta, \phi}(w_t, s_t) = \exp\{f_{\theta, \phi}(w_t, s_t)\}$$  \hspace{1cm} (3)

For convenience, the decision boundary $D$ can be represented as a sigmoid function:

$$D_{\theta, \phi}(w_t, s_t) = \frac{p_{\theta, \phi}(w_t, s_t)}{p_{\theta, \phi}(w_t, s_t) + \pi_\phi(t)} = \text{sigmoid}(f_{\theta, \phi}(w_t, s_t) - \log(\pi_\phi(t)))$$  \hspace{1cm} (4)

In the context of divergence minimization, the adversarial process between the discriminator and the generator can be represented as a two-player min-max game (Mescheder and Geiger, 2017):

$$\min_{\psi} \max_{\theta, \phi} \mathbb{E}_{w_t^{\text{true}}, s_t^{\text{true}}} \left[ \log(D_{\theta, \phi}(w_t^{\text{true}}, s_t^{\text{true}})) \right] + \mathbb{E}_{w_t^{\text{true}}, s_t} \left[ \log(1 - D_{\theta, \phi}(w_t, s_t)) \right]$$  \hspace{1cm} (5)

where $p_{\text{true}}$ is the true word distribution and $w_t^{\text{true}}$ is the ground truth word sampled from the true data. $s_t^{\text{true}}$ is the corresponding state of word $w_t^{\text{true}}$. In the two-player game, the discriminator maximizes the divergence between the true word distribution and the generated vocabulary distribution, whereas the generator minimizes the divergence. The adversarial training reaches Nash equilibrium when the generated vocabulary distribution $\pi_\phi$ approximates the estimated data distribution $p_{\theta, \phi}$, i.e., $D = 0.5$, and both the discriminator and the generator converge. As a result, the discriminator estimates $p_{\theta, \phi}$ that approximates the true word distribution $p_{\text{true}}$, and the generator learns an optimal vocabulary distribution $\pi_\phi$ that maximizes the reward $f_{\theta, \phi}$ from $D_{\theta, \phi}$.

As mentioned before, a compact reward function can precisely tell the contribution of each word and thus help to locate the wrong words. AIRL can learn a compact reward function at optimality in that 1) it disentangles word-wise reward from different image-caption pairs; 2) the reward difference of two words is positively correlated to their semantic difference if AIRL can recover the true reward for each word. However, AIRL is difficult to converge to Nash equilibrium using policy gradient, requiring Hessian of the gradient vector field being positive definite (see details in Section 4.2). When the adversarial training of AIRL is not convergent, apparently the true reward cannot be recovered. As a result, the learned reward function is not compact. Besides, as a GAN based method, AIRL has a sharp decision boundary for two disjoint distributions, which means the discriminator is much stronger than the consequence. The consequence is a limited diversity in the generated captions (see details in Section 4.2), which is called mode collapse in GAN. To solve the two major problems, we explicate in the next section about how we refine the loss function to shift the generator towards Nash equilibrium and to mitigate mode collapse in the two-player game.

4 LEARNING COMPACT REWARD FOR IMAGE CAPTIONING

To address the problems discussed above, we refine the loss function to 1) find a compact reward function that can reach its optimum in the adversarial training; 2) increase diversity of the generated captions. In particular, a constant term is used to solve 1) by shifting the generator to Nash equilibrium, and a conditional term is introduced to solve 2) by utilizing mode control techniques. Our algorithm is detailed in Algorithm 1, where $n$ is the sentence length and $N$ denotes number of iterations.

In the following notations, $\theta$ and $\phi$ are the parameters of the discriminator, and $\psi$ represents the parameter of the generator. $w_t$ and $s_t$ denote the $t_{th}$ word and its corresponding hidden state vector, respectively. For better clarity, policy $\pi_\phi$ is hereinafter referred to as the generated vocabulary distribution.

4.1 Discriminator

The objective of the discriminator is to distinguish the true caption from the generated one. At time $t$, the discriminator maximizes the divergence in Eq. (5) by

$$L_d(\theta, \phi) = -\mathbb{E}_{w_t^{\text{true}}, s_t^{\text{true}}} \left[ \log(D_{\theta, \phi}(w_t^{\text{true}}, s_t^{\text{true}})) \right] - \mathbb{E}_{w_t, s_t} \left[ \log(1 - D_{\theta, \phi}(w_t, s_t)) \right]$$  \hspace{1cm} (6)

where $w_t^{\text{true}}$ is the true word and $s_t^{\text{true}}$ is its corresponding state. The expectation disappears since it is estimated by sampling a mini-batch from the corresponding distribution. $D_{\theta, \phi}$ is computed as in Eq. (4), where the discriminator learns the reward function $f_{\theta, \phi}$ for $D_{\theta, \phi}$ and the generator estimates the vocabulary distribution $\pi_\phi$ for $D_{\theta, \phi}$, respectively.

4.2 Generator

Given a word $w_t$ that is sampled from the vocabulary distribution $\pi_\phi$, the generator maximizes $D_{\theta, \phi}(w_t, s_t)$ by

$$L_g(\psi) = -\mathbb{E}_{w_t, s_t} \left[ \log(D_{\theta, \phi}(w_t, s_t)) - \log(1 - D_{\theta, \phi}(w_t, s_t)) \right]$$  \hspace{1cm} (7)
When the decision boundary \( D \) (black dotted line) reaches its optimum \( D = 0.5 \), it can not distinguish since the generated vocabulary distribution (blue dotted line) approximates the true word distribution (green line). (b) if the Hessian of the generator has not positive definite, gradient from the generator \( \nabla_{\theta} L \), pushes it away from the equilibrium point in (a). Thus the decision boundary can discriminate between the generated vocabulary distribution and the true distribution in the gray area. (c) the discriminator tries to maximize the divergence between the two distributions and deviates from the optimum \( D = 0.5 \). Such dynamics in the AIRL algorithm lead to non-convergence. Our refined algorithm shifts \( \nabla_{\theta} L \) back to 0 and thus converges to Nash Equilibrium as in (a).

Using REINFORCE algorithm (Sutton and Barto, 1998), the gradient \( \nabla_{\theta} L \) becomes:

\[
\nabla_{\theta} L = - \sum_{\pi_\theta} (f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(w_t, s_t))) \nabla_{\theta} \pi_\theta(t)
\]

\[
- \sum_{\pi_\theta} \pi_\theta(w_t, s_t) \nabla_{\theta} (f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)))
\]

\[
= - \sum_{\pi_\theta} \pi_\theta(t) \frac{f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(w_t, s_t))}{\pi_\theta(t)} \nabla_{\theta} \pi_\theta(t)
\]

\[
- \sum_{\pi_\theta} \pi_\theta(t) \nabla_{\theta} (f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)))
\]

\[
= - \sum_{\pi_\theta} \pi_\theta(t) \frac{f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)) - 1}{\pi_\theta(t)} \nabla_{\theta} \pi_\theta(t)
\]

When the decision boundary \( D \) reaches its optimum \( D = 0.5 \), \( f_{\theta,\psi}(w_t, s_t) = \log(\pi_\theta(t)) \) as in Figure 3(a), the generator can only converge when \( \nabla_{\theta} \pi_\theta = 0 \) in Eq. (8), requiring Hessian of the gradient vector field being positive definite (Mescheder and Geiger, 2017). Otherwise, even if the generator has learned the true word distribution \( \log(\pi_\theta(t)) = f_{\theta,\psi}(w_t, s_t) = p_{\text{true}} \), the non-zero gradient \( \nabla_{\theta} L \) from itself still pushes it away from the true word distribution. Thus the decision boundary can discriminate between the generated vocabulary distribution and the true word distribution in the gray area of Figure 3(b). Then the discriminator tries to maximize the divergence between the two distributions and deviates from the optimum \( D = 0.5 \), which leads to the results in Figure 3(c). Such dynamics cause non-convergence in the adversarial training. If the generator converges at \( \log(\pi_\theta(t)) = f_{\theta,\psi}(w_t, s_t) \) instead of \( \nabla_{\theta} \pi_\theta = 0 \) in Eq. (8), then its gradient \( \nabla_{\theta} L \) becomes 0 at \( D = 0.5 \) and the Nash equilibrium in Figure 3(a) can be maintained. Therefore, we introduce a constant term in the expectation in Eq. (7)

\[
L(\psi) = - \mathbb{E}_{w_t, s_t} [f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)) + 1]
\]

Thus, according to Eq. (8), we have

\[
\nabla_{\theta} L = - \frac{1}{\pi_\theta} (f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t))) \nabla_{\theta} \pi_\theta(t)
\]

\[
= \mathbb{E}_{w_t, s_t} [f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)) + 1]
\]

\[
= \mathbb{E}_{w_t, s_t} [f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t))]
\]

\[
= -f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)) \nabla_{\theta} \pi_\theta(t)
\]

\[
= -(f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t))) \log(\pi_\theta(t))
\]

In practice, the discriminator is usually easier to converge than the generator. If the discriminator converges too early, the generated vocabulary distribution hasn’t approximated the true word distribution, which makes them two disjoint distributions. The gradients of \( D \) are thus zero almost everywhere (see Figure 4(a)) (Peng et al., 2019), causing limited diversity of the generated captions. The problem is called mode collapse, meaning that the generator produces a single or limited modes. If the generated vocabulary distribution has some overlap with the true word distribution, then the discriminator can not easily differentiate between them, which makes the decision boundary \( D \) more smooth. Therefore, we introduce ground truth data into the generator as a conditional term (Mirza and Osindero, 2014):

\[
L(\psi) = - \mathbb{E}_{w_t, s_t} [f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t)) + 1]
\]

\[
- \mathbb{E}_{w_t, s_t} [f_{\theta,\psi}(w_t^{\text{true}}, s_t^{\text{true}}) - \log(\pi_\theta^{\text{true}}(t)) + 1]
\]

\[
= -(f_{\theta,\psi}(w_t, s_t) - \log(\pi_\theta(t))) \log(\pi_\theta^{\text{true}}(t))
\]

(12)

where \( \pi_\theta^{\text{true}} \) is the approximated probability of the true word in the generator, and \( \mathbb{E}_{w_t, s_t} [...] \) is the conditional term. To
We compare the formula of the proposed loss function with existing methods in Table 1, including MLE, RL and GAN. $n$ is the length of a sentence. $r$ is the handcrafted metric, such as BLEU, CIDEr and SPICE. $\pi$ is the probability of the $t_{th}$ generated word, and $\pi_{true}$ is the probability of the $t_{th}$ true word. The loss functions are rewritten using similar symbols for direct comparison. MLE maximizes the probability of the true data $\pi_{true}$ whilst RL and GAN optimize the reward by sampling from $\pi$. GAN is different from RL in that its reward is learned from the discriminator adversarially instead of being predefined. GAN is capable of mimicking human-written captions by adversarial learning, but the estimated reward function $D_{gen}$ of a full trajectory can be explained by multiple optimal policies and thus is too ambiguous. The proposed rAIRL further disentangles the reward into $D_{gen}$ at each time step $t$, as well as incorporating the true data for better diversity. From the perspective of loss functions, rAIRL can be regarded as an integration of GAN and the first term of MLE using coefficients $\sigma^{-1}(D_{gen})$ and $\sigma^{-1}(D_{true})$.

### 5 Experiments

In the experiments, we validate the effectiveness of the proposed algorithm by answering two questions: 1) Is the caption evaluator (i.e., discriminator) capable of learning compact reward? 2) Driven by the learned reward, is the caption generator effective to produce qualitative captions? To answer 1), we first tested the compactness of the learned reward by observing performance of the collected top-$k$ captions. Then we explored the correlation between the learned reward and the human evaluation results. To answer 2), we built our algorithm on existing learning methods and compared their performance on conventional evaluation metrics. For a comprehensive evaluation, we also evaluated the quality of the generated caption on its content, diversity and grammar. Besides, ablation experiments were conducted to demonstrate the importance of each component of our algorithm.

#### 5.1 Implementation Details

We conducted experiments on the well-known benchmark datasets MS COCO (Chen et al., 2015) and Flickr30K Young et al. (2014), which have 123,287 and 31,783 labeled images, respectively, and each image has at least 5 human annotated captions as reference. We use the public available split Karpathy and Fei-Fei (2015) for Flickr30K. To assess the robustness of
we implement our algorithm using Adam optimizer (Kingma and Ba, 2015) with fixed learning rate $10^{-5}$. Our vocabulary size is 10,000/7065 for MS COCO and Flickr30K, respectively, including a special start sign `<BOS>' and an end sign `EOS'. In the generator, the number of hidden nodes of every layer is 512. For simplicity, the discriminator has the same model structure as the generator except having one additional layer for estimating $h_x$. For fair comparison, all the methods in ML (Up-Down), RL(Up-Down), GAN(Up-Down), AIRL(Up-Down) and rAIRL(Up-Down) were produced using the same image features and model structure (Up-Down) in (Anderson et al., 2018). Specifically, RL(Up-Down) adopts the self-critical loss in (Rennie et al., 2017). GAN(Up-Down) uses the adversarial loss in (Dai and Lin, 2017) that learns sentence-level reward. AIRL(Up-Down) is the standard adversarial inverse reinforcement learning method in (Fu et al., 2018), and rAIRL(Up-Down) is the proposed method. Note that our scores of MLE(Up-Down) are lower on the standard split but higher on the robust split than (Anderson et al., 2018) because we used fixed number of the bounding box (i.e., 36) for simplicity, and the hyperparameters were tuned to adapt to both splits and thus are not exactly the same with (Anderson et al., 2018).

### 5.2 Performance of the Recovered Reward

In this section, we evaluated the learned reward function on three aspects: compactness, correlation with human evaluation and performance on diagnosing captions. Compactness shows accuracy of the disentangled reward in measuring word semantic. It is evaluated by computing the correlation between the reward differences and semantic differences after replacing specific words in the caption. Correlation with human evaluation indicates how well the caption evaluator correlates with human judgments. It is based on human scores collected by Aditya et al. (2017). Diagnosing captions using the learned reward function can help improving captions, whose performance is evaluated by the relative improvement after diagnosing and re-written.

Table 2: Correlation between the reward differences and semantic differences by replacing a given word with a similar word (RP=S) and a distinct word (RP=D), respectively.

| Method          | Standard Split RP_S | Standard Split RP_D | Robust Split RP_S | Robust Split RP_D |
|-----------------|---------------------|---------------------|-------------------|-------------------|
| RL(Up-Down)     | 0.03                | 0.01                | -0.10             | 0.00              |
| GAN(Up-Down)    | 0.07                | 0.21                | 0.04              | 0.18              |
| AIRL(Up-Down)   | 0.15                | 0.11                | 0.30              | 0.20              |
| rAIRL(Up-Down)  | 0.54                | 0.30                | 0.51              | 0.31              |

**Compactness.** Compactness means that the reward values should be close for similar words and different for distinct words. For example, *kid* can also be referred to as *little boy* or *little girl*, and thus their reward values should be close to each other in the discriminator. To see the correlation between the reward differences and semantic differences, we replace a given word $w_t$ in the generated caption with a similar word $w_{\text{similar}}$ and a distinct word $w_{\text{distinct}}$, respectively. Specifically, in a generated caption, the first word that belongs to the COCO 80 class is replaced. A sentence is discarded if no word can be replaced. The words within the same class are considered to be similar (such as *bike* and *bicycle*), and the words that belong to difference classes are distinct (such as *man* and *bike*). For RL, since it maximizes a handcrafted reward (SPICE (Anderson et al., 2016) in our experiment) instead of learning a reward function, the reward difference is the variation of SPICE before and after replacement. For reward-learning methods, the reward difference is the variation of the learned reward. The semantic difference is the Euclidean distance between the Glove embedding vectors of two words (Pennington et al., 2014). The results are reported in Table 2. Higher correlation indicates better compactness. RL serves as a baseline in that the handcrafted reward SPICE compares n-gram overlapping without considering the semantic difference. The reward differences of rAIRL correlate the best with the semantic differences for both similar words and distinct words, proving the compactness of the learned reward.

It’s also noted that due to the reward ambiguity problem, the reward differences of GAN poorly correlate with the semantic differences, especially for similar words. Figure 5 shows the top-5 generated captions of a given image. Driven by the learned compact reward function, the top-5 cap-

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2 https://github.com/jiasenlu/NeuralBabyTalk/blob/master/data/coco/coco_class_name.txt

**Figure 5:** Examples of the top-5 generated captions of rAIRL. Driven by the compact reward function, the generator describes a given image with semantically similar words.
Correlation with human evaluation. As a caption evaluator, the discriminator learns \( g_{\theta} \) that recovers the true reward up to a constant at optimality (Fu et al., 2018). To explore the correlation between the recovered reward and the human evaluation scores, we used the human scores in the COMPOSITE\(^3\) dataset (Aditya et al., 2017), whose images are subsets from Flickr8k, Flickr30k and MS COCO. The descriptions from this dataset are either ground truth captions or generated sentences by (Aditya et al., 2017; Johnson et al., 2015). In the human evaluation process, the AMT worker was asked to give a score at range of 1-5 to evaluate the correctness and throughness of each sentence. Captions with length exceeding 20 were discarded, resulting a total of 11,657 sentences. Full results of the correlation is shown in Table 3. The correlation is evaluated using Pearson \( \rho \), Kendall’s \( \tau \) and Spearman’s \( r \) correlation coefficients. In Table 3, the reward of AIRL/rAIRL is the sum of the word-wise reward \( g_{\theta} \), and the reward of rAIRL+SPICE is a linear combination of \( g_{\theta} \) and the SPICE score. Among the reward-learning methods, AIRL poorly correlates with human, whereas the proposed rAIRL improves AIRL on all the correlation metrics, especially on the Pearson correlation (from 0.04 to 0.43). Furthermore, a simple combination of SPICE and the recovered reward leads to an increased correlation with the human scores, which proves the capacity of the discriminator as a caption evaluator. We also found that conventional metrics, especially BLEU, do not correlate well with human evaluation in terms of linear correlation. Therefore, in the experiments of evaluating the captions in the next section, we directly adopt human studies as the evaluation method, along with other objective evaluation metrics that have proven to correlate well with human, including SPICE (Anderson et al., 2016), CHAIR, and CHAIR\(_i\) (Rohrbach et al., 2018). Results on the conventional metrics are also reported for comparison with existing methods, but they are not addressed.

Diagnose and improve captions. Since the proposed rAIRL learns a word-wise reward, it’s also applicable to diagnose a given caption by finding the wrong word (e.g., the word whose reward decreases sharply compared with that of the previous word) and rewriting the caption to improve its quality. For example, improving a man is playing soccer to a man and a kid are playing soccer can be done by rewriting the caption from is (see Figure 6 for more examples). Therefore, we choose to rewrite a given caption (source caption) from the word whose reward has a decrease rate larger than 50%. However, we found that even rewriting the source caption from a random position using rAIRL can also improve the evaluation scores. Thus, rewriting from a random position is selected as the baseline to compare with rewriting from the located position. Table 4 shows results of rewriting from the located position, where the source captions are given by MLE, RL, GAN and AIRL. Beside each score we report its improvement relative to rewriting from a random position.

\(^3\)https://imagesdg.wordpress.com/image-to-scene-description-graph/
Figure 6: Examples showing the generated captions from AIRL before and after re-written.

**Before: a black and white bird standing in the sand.**

**After: a black and white bird standing on the edge of a lake.**

**Before: a dog sitting on top of a chair.**

**After: a dog is looking out of a wicker chair.**

Table 5: Comparison with existing methods on the handcrafted evaluation metrics.

| Learning Method | Model       | Standard Split | Robust Split | Flickr30K |
|-----------------|-------------|----------------|--------------|-----------|
|                 |             | BLEU4 | CIDEr | SPICE | BLEU4 | CIDEr | SPICE | BLEU4 | CIDEr | SPICE |
| MLE             | MLE         | 31.3  | 101.3| -     | 31.5  | 90.6  | 17.7  | -     | -     | -     |
|                 | Att2in      | 34.7  | 107.2| 20.1  | 31.7  | 94.1  | 18.3  | 27.1  | 57.5  | 15.6  |
|                 | NBT         | 36.2  | 113.5| 20.3  | 31.6  | 92.0  | 18.1  | -     | -     | -     |
|                 | Up-Down     | 34.6  | 112.9| 20.7  | 31.1  | 96.8  | 19.1  | 29.2  | 58.9  | 15.7  |
|                 | rAIRL+MLE(Up-Down) | 36.2  | 113.5| 20.3  | 31.6  | 92.0  | 18.1  | -     | -     | -     |
| RL              | GAN         | 20.7  | 79.5 | 18.2  | -     | -     | -     | -     | -     | -     |
|                 | Up-Down     | 33.3  | 114.4| -     | -     | -     | -     | -     | -     | -     |
|                 | rAIRL+RL(Up-Down) | 36.3  | 120.1| 21.4  | 30.8  | 97.9  | 19.7  | 28.4  | 57.5  | 15.6  |
| GAN             | G-GAN       | 20.7  | 79.5 | 18.2  | -     | -     | -     | -     | -     | -     |
|                 | GAN3        | 33.3  | 114.4| -     | -     | -     | -     | -     | -     | -     |
|                 | rAIRL(Up-Down) | 36.3  | 120.1| 21.4  | 30.8  | 97.9  | 19.7  | 28.4  | 57.5  | 15.6  |

Table 6: Evaluation scores on generated captions. The best score is in bold font and the second best score is underlined. SPICE is the handcrafted evaluation metric. CHAIR, and CHAIRᵢ, represent the object hallucination ratio at sentence level and instance level, respectively. Human indicates human evaluation.

| Method                  | Standard Split | Robust Split | Human |
|-------------------------|----------------|--------------|-------|
|                         | SPICE | CHAIRₛ | CHAIRᵢ | Human | SPICE | CHAIRₛ | CHAIRᵢ | Human |
| MLE(Up-Down)            | 19.0  | 8.3    | 6.0     | 16.1  | 18.6  | 19.1    | 16.9    | 18.0  |
| RL(Up-Down)             | **20.7** | 11.4   | 8.5     | 8.7   | 18.1  | 25.2    | 20.4    | 6.4   |
| GAN(Up-Down)            | 18.3  | 7.6    | 6.4     | 19.9  | 16.8  | 17.3    | 15.2    | 20.2  |
| AIRL(Up-Down)           | 17.3  | 12.7   | 10.3    | 14.0  | 16.7  | 22.7    | 18.5    | 14.8  |
| rAIRL(Up-Down)          | **20.4** | **7.2** | **5.5** | **41.3** | **18.7** | **17.1** | **14.3** | **40.6** |

Figure 7: An example of the images shown to the human evaluator in the human studies (methods marked in gray are not shown). The captions were produced by MLE, GAN, RL, AIRL and rAIRL methods in a randomized order.

1: A herd of cattle drinking from a pond. (GAN)
2: A herd of cows in the water. (RL)
3: A group of cows standing by a river. (AIRL)
4: A herd of cows grazing in the water. (MLE)
5: A herd of cattle drinking from a river. (rAIRL)

1: A woman in a red shirt holding a cellphone. (MLE)
2: A woman standing in front of a laptop. (GAN)
3: A woman holding a cellphone in her hand. (AIRL)
4: A woman taking a picture of herself in a bathroom. (rAIRL)
5: A woman holding a cell phone in her hand. (RL)
5.3 Evaluation on the Generated Captions

In this section, we evaluated the generated captions mainly on three aspects: content correctness, diversity and grammar. Firstly, the results of the caption generator are compared with existing methods on the handcrafted evaluation metrics: BLEU, CIDEr and SPICE. However, since BLEU and CIDEr do not correlate well with human (Anderson et al., 2016), we choose other metrics to evaluate the captions in the following experiments. For a comprehensive evaluation, diversity and grammar are also considered as representation of the caption quality. Finally, results of the ablation studies are reported to show importance of each component of our algorithm in caption generation.

Comparison with existing methods. Categorized by the loss functions, existing models are divided into three categories in Table 5, and we chose recent proposed methods for comparison: Att2In (Rennie et al., 2017), G-GAN (Dai and Lin, 2017), NBT (Lu et al., 2018), Up-Down (Anderson et al., 2018) and GAN2, GAN3 (Dognin et al., 2019). Although some metrics based on n-gram overlapping (BLEU4, CIDEr) do not correlate well with human, their results are also reported in Table 5 for fair comparison. Among the adversarial methods (GAN category), our rAIRL performs the best on all metrics.

To test the generalizing ability of our algorithm, we also built our algorithm on the non-adversarial based models. The composite models are denoted with rAIRL+MLE and rAIRL+RL. In rAIRL+MLE, the conditional term is replaced by the cross-entropy loss of MLE; in rAIRL+RL, the RL loss is added into the loss function of the generator. In Table 5, our rAIRL+MLE further improves the MLE baseline (i.e., Up-Down using MLE loss) on SPICE, whereas rAIRL+RL does not improve the RL baseline (i.e., Up-Down using RL loss) on these metrics. This is caused by the difficulty of normalizing the learned reward and the handicrafted reward to the same order of magnitude (Shelton Christian, 2001). Although RL shows better performance on MS COCO by directly optimizing the handicrafted metric (CIDEr), we show in the following experiments that the overall quality of its generated descriptions is not as satisfying as it seems, especially on human evaluations and grammar.

Content correctness. For a comprehensive evaluation of the content correctness, the results of both the handicrafted metrics and human studies are shown in Table 6. For the handicrafted metrics, we report scores of SPICE and the recently proposed CHAIR, and CHAIR, since they correlate well with human (Anderson et al., 2016; Rohrbach et al., 2018). SPICE computes similarity with the ground truth captions based on scene graph whilst CHAIR, and CHAIR, indicate ratio of hallucinated objects. Compared with non-adversarial methods (i.e., MLE, RL), existing adversarial net (GAN) does not perform well on SPICE due to the reward ambiguity problem, whereas our rAIRL improves GAN (from 16.8 to 18.7) by disentangling reward for each word, and even outperforms RL (from 18.1 to 18.7) on the robust split. The lowest scores on CHAIR, and CHAIR, suggest that object hallucination is less likely in rAIRL. As for the human evaluation, we randomly selected 500 test images from the standard split and robust split of MS COCO, respectively. The worker was asked “which caption is the best” by given an image with five sentences generated from the adversarial and non-adversarial methods, as shown in Figure 7. The worker was allowed but not encouraged to make multiple choices if he/she thinks these captions are equally correct. The order of captions produced by different methods was randomized. Following (Shetty et al., 2017), each image in the test set was evaluated by 5 workers. Human in Table 6 indicates the percentage of captions that are considered the best among the five methods. The descriptions generated by our rAIRL are considered the best for over 40% images, whilst RL has the lowest scores that are less than 10%. The results of RL on human studies are almost contrary to its performance on the handicrafted metrics in Table 5. This suggests that RL may optimize these metrics in an unintended way such that the scores are improved but the quality of caption is not. On the other hand, by self-learning a reward function, the proposed rAIRL has consistent performance on the human studies and the handicrafted metrics.

Table 7: Evaluation of the diversity on generated captions. The best score is in bold font and the second best score is underlined.

| Method          | Standard Split | Robust Split |
|-----------------|----------------|--------------|
|                 | Vocabulary     | Novel Sentence | Vocabulary | Novel Sentence |
| MLE(Up-Down)    | 12.4           | 49.7         | 12.5        | 58.8         |
| RL(Up-Down)     | 11.4           | 88.5         | 12.7        | 87.3         |
| GAN(Up-Down)    | 13.4           | 75.0         | 15.3        | 75.6         |
| AIRL(Up-Down)   | 12.3           | 67.3         | 15.6        | 73.8         |
| rAIRL(Up-Down)  | **13.6**       | **76.1**     | **15.8**    | **76.5**     |

Diversity. The diversity of captions is evaluated on a corpus level, indicating to what extent the generated captions of different images have diverse expressions. The results are presented in Table 7. Vocabulary Coverage is the number of vocabularies of the generated captions over number of vocabularies of the ground truth captions. Novel Sentence indicates the ratio of sentences that do not appear in the training set. The fact that RL has high ratio of novel sentence (88.5%/87.3%) but low vocabulary coverage (11.4%/12.7%) suggests that it uses high-frequency words (such as “in a”, “of a”) to reconstruct captions that appear to be different from the training set (Li et al., 2019a). Our rAIRL improves AIRL on the diversity metrics and outperforms other learning methods on vocabulary coverage, indicating its capability of generating diverse descriptions on a corpus level. Figure 8 gives two examples showing diversity of the generated caption. The proposed rAIRL recognizes notable differences between two similar images and give diverse descriptions for each image.

Grammar. We used LanguageTool 4 to check grammar of the generated captions. Table 8 shows percentage of sentences that have grammar errors found by LanguageTool: 1) Redundancy means repeated phrases in a sentence; 2) Agreement Error means subject-verb agreement error, such as “people is”; 3) Article Misuse denotes inappropriate usage of indefinite articles, such as using “a” before uncountable nouns or plural words; 4) Incomplete Sentence refers to incomplete sentence that lacks a subject. We found captions produced by RL have the most

4https://languagetool.org
MLE: a closeup of a plate of food.  
RL: a plate of food on a table with a plate.  
GAN: a plate of food on a plate.  
AIRL: a plate of food is on a plate.  
rAIRL: a plate of food on a table.

MLE: a closeup of plates of food on a table.  
RL: a plate of food on a table with a plate.  
GAN: a lunch of food on a plate.  
AIRL: a plate of food on a plate.  
rAIRL: a table topped with plates of food on it.

Figure 8: Examples showing diversity of the captions. The left and right columns show pictures with similar content but different details. The proposed rAIRL successfully recognizes these differences and gives diverse captions.

Table 8: Percentage of different grammar errors found in the generated captions. Re represents Redundancy, AE is Agreement Error, AM denotes Article Misuse and IS is Incomplete Sentence.

| Method          | Standard Split |   |   |   | Robust Split |   |   |   |
|-----------------|----------------|---|---|---|-------------|---|---|---|
|                 | Total          | Re | AE | AM | IS | Total        | Re | AE | AM | IS |
| MLE(Up-Down)    | 0.78           | 0.04 | 0.56 | 0.14 | 0.04 | **0.57**     | 0.04 | 0.26 | 0.16 | 0.10 |
| RL(Up-Down)     | 5.64           | 0.90 | 0   | 3.36 | 1.38 | 4.67         | 0.19 | 0.02 | 3.8  | 0.69 |
| GAN(Up-Down)    | 1.24           | 0.62 | 0.18 | 0.06 | 0.38 | 2.40         | 1.10 | 0.40 | 0.26 | 0.63 |
| AIRL(Up-Down)   | 1.68           | 0.04 | 0.62 | 0.70 | 0.32 | 1.20         | 0.10 | 0.27 | 0.72 | 0.12 |
| rAIRL(Up-Down)  | **0.75**       | 0.14 | 0.20 | 0.21 | 0.20 | **0.57**     | 0.14 | 0.17 | 0.16 | 0.10 |

Table 9: Results of using different model architectures in our method.

| Method | Standard Split |   |   |   | Robust Split |   |   |   |
|--------|----------------|---|---|---|-------------|---|---|---|
|        | BLEU4 | CIDEr | SPICE | BLEU4 | CIDEr | SPICE |
| Attn   | 31.0  | 101.3 | -    | 31.5  | 90.6  | 17.7  |
| rAIRL/Attn | 31.3  | 105.2 | 19.9 | 30.7  | 92.5  | 18.0  |
| Up-Down| 36.2  | 113.5 | 20.3 | 31.6  | 92.0  | 18.1  |
| rAIRL/Up-Down | 33.8  | 110.2 | 20.4 | 30.2  | 93.7  | 18.7  |

grammar errors (5.64% on the standard split and 4.67% on the robust split), especially the Article Misuse. On the other hand, by approximating the true data distribution of each word in the sentence, rAIRL and MLE have the least grammar errors among all learning methods (0.75%/0.78% on the standard split and 0.57%/0.57% on the robust split). We also noticed that each method except rAIRL is biased towards a particular type of grammar error: agreement error in MLE, article misuse in RL, redundancy in GAN, article misuse in AIRL. On both splits, our rAIRL does not appear to be biased towards a specific type of these grammar errors.

Table 9: Results of using different model architectures in our method.

| Method | Standard Split |   |   |   | Robust Split |   |   |   |
|--------|----------------|---|---|---|-------------|---|---|---|
|        | BLEU4 | CIDEr | SPICE | BLEU4 | CIDEr | SPICE |
| Attn   | 31.0  | 101.3 | -    | 31.5  | 90.6  | 17.7  |
| rAIRL/Attn | 31.3  | 105.2 | 19.9 | 30.7  | 92.5  | 18.0  |
| Up-Down| 36.2  | 113.5 | 20.3 | 31.6  | 92.0  | 18.1  |
| rAIRL/Up-Down | 33.8  | 110.2 | 20.4 | 30.2  | 93.7  | 18.7  |

Ablation studies. Theoretically, our algorithm is model-agnostic since it is independent of the design of model architecture. Therefore, we compare the results of using Attn2in (Rennie et al., 2017) and Up-Down (Anderson et al., 2018) model architectures in Table 9, respectively. We report the metrics used in the original paper for fair comparison. The proposed rAIRL mainly improves SPICE on both architectures. We conducted another ablation experiment to understand the importance of each component of our algorithm in caption generation. Specifically, the constant term in Eq. (9) and the conditional term in Eq. (12) is removed, respectively. Scores of all the evaluation techniques mentioned above are presented in Table 10. All the scores have a drop after removing either one of the terms. Comparing these two terms, the constant term seems more important in recognizing objects and relations in the image since removing it has larger drop on SPICE. The larger drop on vocabulary coverage and ratio of novel sentence in the second row indicates that the conditional term plays a significant role in increasing the diversity of the generated captions.
Table 10: Ablation methods of rAIRL. “term1” is the constant term in Eq. (9) and “term2” is the conditional term in Eq. (12). GE denotes grammar error rate. VC denotes vocabulary coverage and NS is the ratio of novel sentence.

| Method                        | Standard Split |                      | Robust Split |                  |                     |
|-------------------------------|----------------|----------------------|--------------|-------------------|---------------------|
|                               | SPICE | CHAIR | CHAIR | VC | NS | GE | SPICE | CHAIR | CHAIR | VC | NS | GE |
| rAIRL(Up-Down, w/o term1)     | 18.8  | 10.5  | 8.2  | 12.8 | 73.5 | 1.07 | 17.0  | 19.9  | 17.5 | 14.1 | 71.6 | 0.95 |
| rAIRL(Up-Down, w/o term2)     | 19.3  | 9.4   | 7.4  | 12.2 | 71.3 | 0.83 | 17.9  | 18.9  | 15.8 | 13.7 | 62.4 | 0.72 |
| rAIRL(Up-Down)                | **20.4** | **7.2** | **5.5** | **13.6** | **76.1** | **0.75** | **18.7** | **17.1** | **14.3** | **15.8** | **76.5** | **0.57** |

Figure 9: Captions produced by different methods from the test set (standard split). Beside each caption we report SPICE score. Captions generated by rAIRL are correct and human-like in these examples.

Figure 10: Failed examples of rAIRL. The objects and relations are not correctly recognized in these pictures.
Visualized examples. A few examples of the generated captions produced by different methods are shown in Figures 9 and 10. We compare the captioning results of rAIRL with three other methods: MLE, RL, and GAN. Figure 9 gives successful examples, especially on captioning relations between objects. Figure 10 shows failed examples, where objects and relations are not correctly recognized by the captioning model.

Summary. Through extensive experiments on caption generation, we proved that the proposed rAIRL constantly performs well on both splits of MS COCO. Compared with RL, rAIRL optimizes the learned reward instead of the handcrafted metrics, and is capable of producing qualitative captions with few grammar errors. As an adversarial algorithm, rAIRL enhances GAN by disentangling compact reward for each word in the caption and improves AIRL by shifting the generator towards Nash equilibrium.

6 Conclusion

In this paper, we address the reward ambiguity problem in image captioning and propose a refined Adversarial Inverse Reinforcement Learning (rAIRL) method that solves the problem by disentangling reward for each word in a sentence. Moreover, it achieves stable adversarial training by refining the loss function to shift the generator towards Nash equilibrium, and mode control technique is incorporated to mitigate mode collapse. It is demonstrated that our method can learn compact reward through extensive experiments on MS COCO and Flickr30K.

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