Deep Generative Models with Learnable Knowledge Constraints

Zhiting Hu, Zichao Yang, Ruslan Salakhutdinov, Xiaodan Liang, Lianhui Qin, Haoye Dong, Eric P. Xing
Carnegie Mellon University, Petuum Inc.
{zhitingh,zichaoy,rsalakhu,xiaodan1}@cs.cmu.edu, eric.xing@petuum.com

Abstract

The broad set of deep generative models (DGMs) has achieved remarkable advances. However, it is often difficult to incorporate rich structured domain knowledge with the end-to-end DGMs. Posterior regularization (PR) offers a principled framework to impose structured constraints on probabilistic models, but has limited applicability to the diverse DGMs that can lack a Bayesian formulation or even explicit density evaluation. PR also requires constraints to be fully specified a priori, which is impractical or suboptimal for complex knowledge with learnable uncertain parts. In this paper, we establish mathematical correspondence between PR and reinforcement learning (RL), and, based on the connection, expand PR to learn constraints as the extrinsic reward in RL. The resulting algorithm is model-agnostic to apply to any DGMs, and is flexible to adapt arbitrary constraints with the model jointly. Experiments on human image generation and templated sentence generation show models with learned knowledge constraints by our algorithm greatly improve over base generative models.

1 Introduction

Generative models provide a powerful mechanism for learning data distributions and simulating samples. Recent years have seen remarkable advances especially on the deep approaches\cite{16, 25} such as Generative Adversarial Networks (GANs)\cite{15}, Variational Autoencoders (VAEs)\cite{27}, auto-regressive networks\cite{29, 42}, and so forth. However, it is usually difficult to exploit in these various deep generative models rich problem structures and domain knowledge (e.g., the human body structure in image generation, Figure[1]). Many times we have to hope the deep networks can discover the structures from massive data by themselves, leaving much valuable domain knowledge unused. Recent efforts of designing specialized network architectures or learning disentangled representations\cite{5, 23} are usually only applicable to specific knowledge, models, or tasks. It is therefore highly desirable to have a general means of incorporating arbitrary structured knowledge with any types of deep generative models in a principled way.

On the other hand, posterior regularization (PR)\cite{13} is a principled framework to impose knowledge constraints on posterior distributions of probabilistic models, and has shown effectiveness in regulating the learning of models in different context. For example,\cite{21} extends PR to incorporate structured logic rules with neural classifiers. However, the previous approaches are not directly applicable to the general case of deep generative models, as many of the models (e.g., GANs, many auto-regressive networks) are not straightforwardly formulated with the probabilistic Bayesian framework and do not possess a posterior distribution or even meaningful latent variables. Moreover, PR has required a priori fixed constraints. That means users have to fully specify the constraints beforehand, which can be impractical due to heavy engineering, or suboptimal without adaptivity to the data and models. To extend the scope of applicable knowledge and reduce engineering burden, it is necessary to allow
users to specify only partial or fuzzy structures, while learning remaining parts of the constraints jointly with the regulated model.

To this end, we establish formal connections between the PR framework with a broad set of algorithms in the control and reinforcement learning (RL) domains, and, based on the connections, transfer well-developed RL techniques for constraint learning in PR. In particular, though the PR framework and the RL are apparently distinct paradigms applied in different context, we show mathematical correspondence between the model and constraints in PR with the policy and reward in entropy-regularized policy optimization \[ 43, 45, 1 \], respectively. This thus naturally inspires to leverage relevant approach from the RL domain (specifically, the maximum entropy inverse RL \[ 56, 11 \]) to learn the PR constraints from data (i.e., demonstrations in RL).

Based on the unified perspective, we drive a practical algorithm with efficient estimations and moderate approximations. The algorithm is efficient to regularize large target space with arbitrary constraints, flexible to couple adapting the constraints with learning the model, and model-agnostic to apply to diverse deep generative models, including implicit models where generative density cannot be evaluated \[ 40, 15 \]. We demonstrate the effectiveness of the proposed approach in both image and text generation (Figure 1). Leveraging domain knowledge of structure-preserving constraints, the resulting models improve over base generative models.

2 Related Work

It is of increasing interest to incorporate problem structures and domain knowledge in machine learning approaches \[ 49, 13, 21 \]. The added structure helps to facilitate learning, enhance generalization, and improve interpretability. For deep neural models, one of the common ways is to design specialized network architectures or features for specific tasks (e.g., \[ 2, 34, 28, 33 \]). Such a method typically has a limited scope of applicable tasks, models, or knowledge. On the other hand, for structured probabilistic models, posterior regularization (PR) and related frameworks \[ 13, 32, 4 \] provide a general means to impose knowledge constraints during model estimation. \[ 21 \] develops iterative knowledge distillation based on PR to regularize neural networks with any logic rules. However, the application of PR to the broad class of deep generative models has been hindered, as many of the models do not even possess meaningful latent variables or explicit density evaluation (i.e., implicit models). Previous attempts thus are limited to applying simple max-margin constraints \[ 31 \]. The requirement of a priori fixed constraints has also made PR impractical for complex, uncertain knowledge. Previous efforts to alleviate the issue either require additional manual supervision \[ 59 \] or is limited to regularizing small label space \[ 22 \]. This paper develops a practical algorithm that is generally applicable to any deep generative models and any learnable constraints on arbitrary (large) target space.

Our work builds connections between the Bayesian PR framework and reinforcement learning. A relevant, broad research topic of formalizing RL as a probabilistic inference problem has been explored in the RL literature \[ 6, 7, 41, 30, 1, 48 \], where rich approximate inference tools are used to improve the modeling and reasoning for various RL algorithms. The link between RL and PR
A straightforward way to impose the constraint on the model is to maximize
we present in the generative model context, the formulations, including the algorithm developed later
sec 4), can straightforwardly be extended to other settings such as discriminative models.

Table 1: Unified perspective of the different approaches, showing mathematical correspondence of PR with the entropy-regularized RL (sec 3.2.1) and maximum entropy IRL (sec 3.2.2), and its (conceptual) relations to (energy-based) GANs (sec 4).

has not been previously studied. We establish the mathematical correspondence, and, differing from
the RL literature, we in turn transfer the tools from RL to expand the probabilistic PR framework.
Recent approaches based on maximum-entropy IRL [50] are developed to learn both the reward and
objective in our algorithm, and leverage the unique structure of PR for efficient importance sampling
estimation, which differs from these previous approaches.

3 Connecting Posterior Regularization to Reinforcement Learning

3.1 PR for Deep Generative Models

PR [13] was originally proposed to provide a principled framework for incorporating constraints on
posterior distributions of probabilistic models with latent variables. The formulation is not generally
applicable to deep generative models as many of them (e.g., GANs and autoregressive models) are not
formulated within the Bayesian framework and do not possess a valid posterior distribution or even
semantically meaningful latent variables. Here we adopt a slightly adapted formulation that makes
minimal assumptions on the specifications of the model to regularize. It is worth noting that though
we present in the generative model context, the formulations, including the algorithm developed later
sec 4), can straightforwardly be extended to other settings such as discriminative models.

Consider a generative model \( x \sim p_\theta(x) \) with parameters \( \theta \). Note that generation of \( x \) can condition
on arbitrary other elements (e.g., the source image for image transformation) which are omitted for
simplicity of notations. Denote the original objective of \( p_\theta(x) \) with \( \mathcal{L}(\theta) \). PR augments the objective
by adding a constraint term encoding the domain knowledge. Without loss of generality, consider
constraint function \( f(x) \in \mathbb{R} \), such that a higher \( f(x) \) value indicates a better \( x \) in terms of the
particular knowledge. Note that \( f \) can also involve other factors such as latent variables and extra
supervisions, and can include a set of multiple constraints.

A straightforward way to impose the constraint on the model is to maximize \( \mathbb{E}_{p_\theta} [f(x)] \). Such method
is efficient only when \( p_\theta \) is a GAN-like implicit generative model or an explicit distribution that
can be efficiently reparameterized (e.g., Gaussian [27]). For other models such as the large set of
non-reparameterizable explicit distributions, the gradient \( \nabla_\theta \mathbb{E}_{p_\theta} [f(x)] \) is usually computed with the
log-derivative trick and can suffer from high variance. For broad applicability and efficient
optimization, PR instead imposes the constraint on an auxiliary variational distribution \( q \), which is
couraged to stay close to \( p_\theta \) through a KL divergence term:

\[
\mathcal{L}(\theta, q) = \text{KL}(q(x)||p_\theta(x)) - \alpha \mathbb{E}_q[f(x)],
\]

where \( \alpha \) is the weight of the constraint term. The PR objective for learning the model is written as:

\[
\min_{\theta, q} \mathcal{L}(\theta) + \lambda \mathcal{L}(\theta, q),
\]

where \( \lambda \) is the balancing hyperparameter. As optimizing the original model objective \( \mathcal{L}(\theta) \) is
straightforward and depends on the specific generative model of choice, in the following we omit the
discussion of \( \mathcal{L}(\theta) \) and focus on \( \mathcal{L}(\theta, q) \) introduced by the framework.

The problem is solved using an EM-style algorithm [13, 21]. Specifically, the E-step optimizes Eq. (1)
w.r.t \( q \), which is convex and has a closed-form solution at each iteration given \( \theta \):

\[
q^*(x) = p_\theta(x) \exp \{ \alpha f(x) \} / Z,
\]

3
where $Z$ is the normalization term. We can see $q^*$ as an energy-based distribution with the negative energy defined by $\alpha f(x) + \log p_\theta(x)$. With $q$ from the E-step fixed, the M-step optimizes Eq. (1) w.r.t $\theta$ with:

$$\min_\theta KL(q(x)||p_\theta(x)) = \min_\theta -E_q[\log p_\theta(x)] + \text{const.} \quad (4)$$

Constraint $f$ in PR has to be fully-specified a priori and is fixed throughout the learning. It would be desirable or even necessary to enable learnable constraints so that practitioners are allowed to specify only the known components of $f$ while leaving any unknown or uncertain components automatically learned. For example, for human image generation in Figure 1 left panel, users are able to specify structures on the parsed human parts, while it is impractical to also manually engineer the human part parser that involves recognizing parts from raw image pixels. It is favorable to instead cast the parser as a learnable module in the constraint. Though it is possible to pre-train the module and simply fix in PR, the lack of adaptivity to the data and model can lead to suboptimal results, as shown in the empirical study (Table 2). This necessitates to expand the PR framework to enable joint learning of constraints with the model.

Denote the constraint function with learnable components as $f_\phi(x)$, where $\phi$ can be of various forms that are optimizable, such as the free parameters of a structural model, or a graph structure to optimize.

**Simple way of learning the constraint.** A straightforward way to learn the constraint is to directly optimize Eq. (1) w.r.t $\phi$ in the M-step, yielding

$$\max_\phi E_{x \sim q(x)}[f_\phi(x)]. \quad (5)$$

That is, the constraint is trained to fit to the samples from the current regularized model $q$. However, such objective can be problematic as the generated samples can be of low quality, e.g., due to poor state of the generative parameter $\theta$ at initial stages, or insufficient capability of the generative model per se.

In this paper, we propose to treat the learning of constraint as an extrinsic reward, as motivated by the connections between PR with the reinforcement learning domain presented below.

### 3.2 PR and RL

RL or optimal control has been studied primarily for determining optimal action sequences or strategies, which is significantly different from the context of PR that aims at regulating generative models. However, formulations very similar to PR (e.g., Eqs.[1] and [3]) have been developed and widely used, in both the (forward) RL for policy optimization and the inverse RL for reward learning.

To make the mathematical correspondence clearer, we intentionally re-use most of the notations from PR. Table 1 lists the correspondence. Specifically, consider a stationary Markov decision process (MDP). An agent in state $s$ draws an action $a$ following the policy $p_\pi(a|s)$. The state subsequently transfers to $s'$ (with some transition probability of the MDP), and a reward is obtained $R(s,a) \in \mathbb{R}$. Let $x = (s,a)$ denote the state-action pair, and $p_\pi(x) = \mu_\pi(s)p_\pi(a|s)$ where $\mu_\pi(s)$ is the stationary state distribution [47].

#### 3.2.1 Entropy regularized policy optimization

The goal of policy optimization is to find the optimal policy that maximizes the expected reward. The rich research line of entropy regularized policy optimization has augmented the objective with information theoretic regularizers such as KL divergence between the new policy and the old policy for stabilized learning. With a slight abuse of notations, let $q_\pi(x)$ denote the new policy and $p_\pi(x)$ the old one. A prominent algorithm for example is the relative entropy policy search (REPS) [43] which follows the objective:

$$\min_{q_\pi} \mathcal{L}(q_\pi) = KL(q_\pi(x)||p_\pi(x)) - \alpha E_{q_\pi}[R(x)], \quad (6)$$

where the KL divergence prevents the policy from changing too rapidly. Similar objectives have also been widely used in other workhorse algorithms such as trust-region policy optimization (TRPO) [45], soft Q-learning [17] [46], and others.

We can see the close resemblance between Eq. (6) with the PR objective in Eq. (1), where the generative model $p_\theta(x)$ in PR corresponds to the reference policy $p_\pi(x)$, while the constraint $f(x)$ corresponds...
We have formally related PR to the RL methods. With the unified view of these approaches, we present the resulting full algorithm in the next section. Table 1 summarizes the correspondence while the above policy optimization algorithms have assumed a reward function given by the external process (sec 5). Moreover, using \( p_\theta \) as the proposal distribution allows \( p_\theta \) to be an implicit generative model (as no likelihood evaluation of \( p_\theta \) is needed). Note that the importance sampling estimation is consistent yet biased.

### 3.2.2 Maximum entropy inverse reinforcement learning

Maximum entropy (MaxEnt) IRL [56] is among the most widely-used methods that induce the reward function from expert demonstrations \( x \sim p_\theta(x) \), where \( p_\theta \) is the empirical demonstration (data) distribution. MaxEnt IRL adopts the same principle as the above entropy regularized RL (Eq.6) that maximizes the expected reward regularized by the relative entropy (i.e., the KL), except that, in MaxEnt IRL, \( p_\pi \) is replaced with a uniform distribution and the regularization reduces to the entropy of \( q_\phi \). Therefore, same as above, the optimal policy takes the form \( \exp(\alpha R(x)) / Z \). MaxEnt IRL assumes the demonstrations are drawn from the optimal policy. Learning the reward function \( R_\phi(x) \) with unknown parameters \( \phi \) is then cast as maximizing the likelihood of the distribution \( q_\phi(x) := \exp(\alpha R_\phi(x))/Z_\phi \):

\[
\phi^* = \arg \max_{\phi} E_{x \sim p_\theta} [\log q_\phi(x)].
\]

Given the direct correspondence between the policy \( q_\phi^* \) in MaxEnt IRL and the policy optimization solution \( q_\pi^* \) of Eq.6, plus the connection between the regularized distribution \( q_\pi^* \) of PR (Eq.3) and \( q_\phi^* \) as built in sec 3.2.1, we can readily link \( q^* \) and \( q_\phi^* \). This motivates to plug \( q^* \) in the above maximum likelihood objective to learn the constraint \( f_\phi \) which is parallel to the reward function \( R_\phi(x) \).

We present the resulting full algorithm in the next section. Table 1 summarizes the correspondence between PR, entropy regularized policy gradient, and maximum entropy IRL.

### 4 Algorithm

We have formally related PR to the RL methods. With the unified view of these approaches, we derive a practical algorithm for arbitrary learnable constraints on any deep generative models. The algorithm alternates the optimization of the constraint \( f_\phi \) and the generative model \( p_\theta \).

#### 4.1 Learning the Constraint \( f_\phi \)

As motivated in section 3.2 instead of directly optimizing \( f_\phi \) in the original PR objectives (Eq.5) which can be problematic, we treat \( f_\phi \) as the reward function to be induced with the MaxEnt IRL framework. That is, we maximize the data likelihood of \( q(x) \) (Eq.3) w.r.t \( \phi \), yielding the gradient:

\[
\nabla_\phi E_{x \sim p_\theta} [\log q(x)] = \nabla_\phi \left[ E_{x \sim p_\theta} [\alpha f_\phi(x)] - \log Z_\phi \right] \\
= E_{x \sim p_\theta} [\alpha \nabla_\phi f_\phi(x)] - E_{q(x)} [\alpha \nabla_\phi f_\phi(x)].
\]

The second term involves estimating the expectation w.r.t an energy-based distribution \( E_{q(x)}[\cdot] \), which is in general very challenging. However, we can exploit the special structure of \( q \propto p_\theta \exp\{\alpha f_\phi\} \) for efficient approximation. Specifically, we use \( p_\theta \) as the proposal distribution, and obtain the importance sampling estimate of the second term as following:

\[
E_{q(x)} [\alpha \nabla_\phi f_\phi(x)] = E_{x \sim p_\theta} \left[ \frac{q(x)}{p_\theta(x)} \cdot \alpha \nabla_\phi f_\phi(x) \right] \\
= 1/Z_{\phi} \cdot E_{x \sim p_\theta} \left[ \exp\{\alpha f_\phi(x)\} \cdot \alpha \nabla_\phi f_\phi(x) \right].
\]

Note that the normalization \( Z_\phi = \int p_\theta(x) \exp\{\alpha f_\phi(x)\} \) can also be estimated efficiently with MC sampling: \( Z_\phi = 1/N \sum_n \exp\{\alpha f_\phi(x_n)\} \), where \( x_n \sim p_\theta \). The base generative distribution \( p_\theta \) is a natural choice for the proposal as it is in general amenable to efficient sampling, and is close to \( q \) as forced by the KL divergence in Eq.(1). Our empirical study shows low variance of the learning process (sec 5). Moreover, using \( p_\theta \) as the proposal distribution allows \( p_\theta \) to be an implicit generative model (as no likelihood evaluation of \( p_\theta \) is needed). Note that the importance sampling estimation is consistent yet biased.
4.2 Learning the Generative Model \(p_\theta\)

Given the current parameter state \((\theta = \theta^t, \phi = \phi^t)\), and \(q(x)\) evaluated at the parameters, we continue to update the generative model. Recall that optimization of the generative parameter \(\theta\) is performed by minimizing the KL divergence in Eq.\((4)\), which we replicate here:

\[
\min_\theta \text{KL}(q(x)||p_\theta(x)) = \min_\theta -E_{q(x)} \left[ \log p_\theta(x) \right] + \text{const.} \tag{10}
\]

The expectation w.r.t \(q(x)\) can be estimated as above (Eq.\(9)\). A drawback of the objective is the requirement of evaluating the generative density \(p_\theta(x)\), which is incompatible to the emerging implicit generative models \([40]\) that only permit simulating samples but not evaluating density.

To address the restriction, when it comes to regularizing implicit models, we propose to instead minimize the reverse KL divergence:

\[
\min_\theta \text{KL}(p_\theta(x)||q(x)) = \min_\theta \mathbb{E}_{p_\theta} \left[ \log \frac{p_\theta(x) \cdot Z_{\phi^t}}{p_\theta(x) \cdot \exp(\alpha f_{\phi^t}(x))} \right] \tag{11}
\]

\[
= \min_\theta -\mathbb{E}_{p_\theta} \left[ \alpha f_{\phi^t}(x) \right] + \text{const}
\]

By noting that \(\nabla_\theta \text{KL}(p_\theta||p_{\theta^t}) \big|_{\theta=\theta^t} = 0\), we obtain the gradient w.r.t \(\theta\):

\[
\nabla_\theta \text{KL}(p_\theta(x)||q(x)) \big|_{\theta=\theta^t} = -\nabla_\theta \mathbb{E}_{p_\theta} \left[ \alpha f_{\phi^t}(x) \right] \big|_{\theta=\theta^t} \tag{12}
\]

That is, the gradient of minimizing the reversed KL divergence equals the gradient of maximizing \(\mathbb{E}_{p_\theta} \left[ \alpha f_{\phi^t}(x) \right]\). Intuitively, the objective encourages the generative model \(p_\theta\) to generate samples that the constraint function assigns high scores. Though the objective for implicit model deviates the original PR framework, reversing KL for computationality was also used previously such as in the classic wake-sleep method \([19]\). The resulting algorithm also resembles the adversarial learning in GANs, as we discuss in the next section. Empirical results on implicit models show the effectiveness of the objective.

The resulting algorithm is summarized in Alg.\(1\).

**Algorithm 1 Joint Learning of Deep Generative Model and Constraints**

**Input:** The base generative model \(p_\theta(x)\)

- The (set of) constraints \(f_{\phi^t}(x)\)

1: Initialize generative parameter \(\theta\) and constraint parameter \(\phi\)
2: repeat
3: Optimize constraints \(\phi\) with Eq.\(3)\)
4: if \(p_\theta\) is an implicit model then
5: Optimize model \(\theta\) with Eq.\(12)\) along with minimizing original model objective \(L(\theta)\)
6: else
7: Optimize model \(\theta\) with Eq.\(10)\) along with minimizing \(L(\theta)\)
8: end if
9: until convergence

**Output:** Jointly learned generative model \(p_{\theta^*}(x)\) and constraints \(f_{\phi^*}(x)\)

---

**Connections to adversarial learning** For implicit generative models, the two objectives w.r.t \(\phi\) and \(\theta\) (Eq.\(8)\) and Eq.\(12)\) are conceptually similar to the adversarial learning in GANs \([15]\) and the variants such as energy-based GANs \([26,55,54,50]\). Specifically, the constraint \(f_\phi(x)\) can be seen as being optimized to assign lower energy (with the energy-based distribution \(q(x)\)) to real examples from \(p_\mu(x)\), and higher energy to fake samples from \(q(x)\) which is the regularized model of the generator \(p_\theta(x)\). In contrast, the generator \(p_\theta(x)\) is optimized to generate samples that confuse \(f_\phi\) and obtain lower energy. Such adversarial relation links the PR constraint \(f_\phi(x)\) to the discriminator in GANs (Table \(1)\). Note that here fake samples are generated from \(q(x)\) and \(p_\theta(x)\) in the two learning phases, respectively, which differs from previous adversarial methods for energy-based model estimation that simulate only from a generator. Besides, distinct from the discriminator-centric view of the previous work \([26,54,50]\), we primarily aim at improving the generative model by incorporating learned constraints. Last but not the least, as discussed in sec \(3.1\), the proposed framework and algorithm are more generally and efficiently applicable to not only implicit generative models as in GANs, but also (non-)reparameterizable explicit generative models.
5 Experiments

We demonstrate the applications and effectiveness of the algorithm in two tasks related to image and text generation [24], respectively.

| Method                  | SSIM   | Human |
|-------------------------|--------|-------|
| 1 Ma et al. [38]        | 0.614  | —     |
| 2 Pumarola et al. [44]  | 0.747  | —     |
| 3 Ma et al. [37]        | 0.762  | —     |
| 4 Base model            | 0.676  | 0.03  |
| 5 With fixed constraint | 0.679  | 0.12  |
| 6 With learned constraint| 0.727  | 0.77  |

Table 2: Results of image generation on Structural Similarity (SSIM) [52] between generated and true images, and human survey where the full model yields better generations than the base models (Rows 5-6) on 77% test cases. See the text for more results and discussion.

5.1 Pose Conditional Person Image Generation

Given a person image and a new body pose, the goal is to generate an image of the same person under the new pose (Figure 4, left). The task is challenging due to body self-occlusions and many cloth and shape ambiguities. Complete end-to-end generative networks have previously failed [37] and existing work designed specialized generative processes or network architectures [37, 44, 38]. We show that with an added body part consistency constraint, a plain end-to-end generative model can also be trained to produce highly competitive results, significantly improving over base models that do not incorporate the problem structure.

Setup. We follow the previous work [37] and obtain from DeepFashion [35] a set of triples (source image, pose keypoints, target image) as supervision data. The base generative model \( p_\theta \) is an implicit model that transforms the input source and pose directly to the pixels of generated image (and hence defines a Dirac-delta distribution). We use the residual block architecture [51] widely-used in image generation for the generative model. The base model is trained to minimize the L1 distance loss between the real and generated pixel values, as well as to confuse a binary discriminator that distinguishes between the generation and the true target image.

Knowledge constraint. Neither the pixel-wise distance nor the binary discriminator loss encode any task structures. We introduce a structured consistency constraint \( f_\phi \) that encourages each of the body parts (e.g., head, legs) of the generated image to match the respective part of the true image. Specifically, the constraint \( f_\phi \) includes a human parsing module that classifies each pixel of a person image into possible body parts. The constraint then evaluates cross entropies of the per-pixel part
Table 3: Sentence generation results on test set perplexity and human survey. Samples by the full model are considered as of higher quality in 24% cases.

| Model                              | Perplexity | Human |
|------------------------------------|------------|-------|
| 1 Base model                       | 30.30      | 0.19  |
| 2 With binary D                    | 30.01      | 0.20  |
| 3 With constraint updated in M-step (Eq.5) | 31.27      | 0.15  |
| 4 With learned constraint          | 28.69      | 0.24  |

Table 4: Two test examples, including the template, the sample by the base model, and the sample by the constrained model.

| Model | Perplexity | Human |
|-------|------------|-------|
| 1 Base model | 30.30 | 0.19 |
| 2 With binary D | 30.01 | 0.20 |
| 3 With constraint updated in M-step (Eq.5) | 31.27 | 0.15 |
| 4 With learned constraint | 28.69 | 0.24 |

acting
the acting is the acting.
the acting is also very good.

out of 10.
10 out of 10.
I will give the movie 7 out of 10.

Table 4: Two test examples, including the template, the sample by the base model, and the sample by the constrained model.
is all we have to specify, while the unknown parameters $\phi$ are learned jointly with the generative model. Despite the simplicity, the empirical results show the usefulness of the constraint.

**Results.** Table 3 shows the results. Row 2 is the base model with an additional binary discriminator that adversarially distinguishes between the generated sentence and the ground truth (i.e., a GAN model). Row 3 is the base model with the constraint learned in the direct way through Eq.(5). We see that the improper learning method for the constraint harms the model performance, partially because of the relatively low-quality model samples the constraint is trained to fit. In contrast, the proposed algorithm effectively improves the model results. Its superiority over the binary discriminator (Row 2) shows the usefulness of incorporating problem structures. Table 4 demonstrates samples by the base and constrained models. Without the explicit constraint forcing in-filling content matching, the base model tends to generate less meaningful content (e.g., duplications, short and general expressions).

6 Discussions: Combining Structured Knowledge with Black-box NNs

We revealed the connections between posterior regularization and reinforcement learning, which motivates to learn the knowledge constraints in PR as reward learning in RL. The resulting algorithm is generally applicable to any deep generative models, and flexible to learn the constraints and model jointly. Experiments on image and text generation showed the effectiveness of the algorithm.

The proposed algorithm, along with the previous work (e.g., [21, 22, 18, 36, 23]), represents a general means of adding (structured) knowledge to black-box neural networks by devising knowledge-inspired losses/constraints that drive the model to learn the desired structures. This differs from the other popular way that embeds domain knowledge into specifically-designed neural architectures (e.g., the knowledge of translation-invariance in image classification is hard-coded in the conv-pooling architecture of ConvNet). While the specialized neural architectures can usually be very effective to capture the designated knowledge, incorporating knowledge via specialized losses enjoys the advantage of generality and flexibility:

- **Model-agnostic.** The learning framework is applicable to neural models with any architectures, e.g., ConvNets, RNNs, and other specialized ones [21].
- **Richer supervisions.** Compared to the conventional end-to-end maximum likelihood learning that usually requires fully-annotated or paired data, the knowledge-aware losses provide additional supervisions based on, e.g., structured rules [21], other models [18, 22, 53, 20], and datasets for other related tasks (e.g., the human image generation method in Figure 1 and [23]). In particular, [23] leverages datasets of sentence sentiment and phrase tense to learn to control the both attributes (sentiment and tense) when generating sentences.
- **Modularized design and learning.** With the rich sources of supervisions, design and learning of the model can still be simple and efficient, because each of the supervision sources can be formulated independently to each other and each forms a separate loss term. For example, [23] separately learns two classifiers, one for sentiment and the other for tense, on two separate datasets, respectively. The two classifiers carry respective semantic knowledge, and are then jointly applied to a text generation model for attribute control. In comparison, mixing and hard-coding multiple knowledge in a single neural architecture can be difficult and quickly becoming impossible when the number of knowledge increases.
- **Generation with discrimination knowledge.** In generation tasks, it can sometimes be difficult to incorporate knowledge directly in the generative process (or model architecture), i.e., defining how to generate. In contrast, it is often easier to instead specify a evaluation metric that measures the quality of a given sample in terms of the knowledge, i.e., defining what desired generation is. For example, in the human image generation task (Figure 1), evaluating the structured human part consistency could be easier than designing a generator architecture that hard-codes the structured generation process for the human parts.

It is worth noting that the two paradigms are not mutually exclusive. A model with knowledge-inspired specialized architecture can still be learned by optimizing knowledge-inspired losses. Different types of knowledge can be best fit for either architecture hard-coding or loss optimization. It would be interesting to explore the combination of both in the above tasks and others.
Acknowledgment This material is based upon work supported by the National Science Foundation grant IIS1563887. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

[1] A. Abdolmaleki, J. T. Springenberg, Y. Tassa, R. Munos, N. Heess, and M. Riedmiller. Maximum a posteriori policy optimisation. In ICLR, 2018.

[2] J. Andreas, M. Rohrbach, T. Darrell, and D. Klein. Learning to compose neural networks for question answering. arXiv preprint arXiv:1601.01705, 2016.

[3] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473, 2014.

[4] K. Bellare, G. Druck, and A. McCallum. Alternating projections for learning with expectation constraints. In UAI, pages 43–50. AUAI Press, 2009.

[5] X. Chen, Y. Duan, R. Houthooft, J. Schulman, I. Sutskever, and P. Abbeel. InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets. In NIPS, 2016.

[6] P. Dayan and G. E. Hinton. Using expectation-maximization for reinforcement learning. Neural Computation, 9(2):271–278, 1997.

[7] M. P. Deisenroth, G. Neumann, J. Peters, et al. A survey on policy search for robotics. Foundations and Trends® in Robotics, 2(1–2):1–142, 2013.

[8] Q. Diao, M. Qiu, C.-Y. Wu, A. J. Smola, J. Jiang, and C. Wang. Jointly modeling aspects, ratings and sentiments for movie recommendation (JMARS). In KDD, pages 193–202. ACM, 2014.

[9] W. Fedus, I. Goodfellow, and A. M. Dai. MaskGAN: Better text generation via filling in the _._. arXiv preprint arXiv:1801.07736, 2018.

[10] C. Finn, P. Christiano, P. Abbeel, and S. Levine. A connection between generative adversarial networks, inverse reinforcement learning, and energy-based models. arXiv preprint arXiv:1611.03852, 2016.

[11] C. Finn, S. Levine, and P. Abbeel. Guided cost learning: Deep inverse optimal control via policy optimization. In ICML, pages 49–58, 2016.

[12] J. Fu, K. Luo, and S. Levine. Learning robust rewards with adversarial inverse reinforcement learning. arXiv preprint arXiv:1710.11248, 2017.

[13] K. Ganchev, J. Gillenwater, B. Taskar, et al. Posterior regularization for structured latent variable models. JMLR, 11(Jul):2001–2049, 2010.

[14] K. Gong, X. Liang, X. Shen, and L. Lin. Look into person: Self-supervised structure-sensitive learning and a new benchmark for human parsing. In CVPR, pages 6757–6765, 2017.

[15] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In NIPS, pages 2672–2680, 2014.

[16] I. Goodfellow, Y. Bengio, and A. Courville. Deep Learning. MIT Press, 2016. http://www.deeplearningbook.org

[17] T. Haarnoja, H. Tang, P. Abbeel, and S. Levine. Reinforcement learning with deep energy-based policies. arXiv preprint arXiv:1702.08165, 2017.

[18] G. Hinton, O. Vinyals, and J. Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

[19] G. E. Hinton, P. Dayan, B. J. Frey, and R. M. Neal. The “wake-sleep” algorithm for unsupervised neural networks. Science, 268(5214):1158, 1995.

[20] A. Holtzman, J. Buys, M. Forbes, A. Bosselut, D. Golub, and Y. Choi. Learning to write with cooperative discriminators. In ACL, 2018.

[21] Z. Hu, X. Ma, Z. Liu, E. Hovy, and E. Xing. Harnessing deep neural networks with logic rules. In ACL, 2016.
[22] Z. Hu, Z. Yang, R. Salakhutdinov, and E. P. Xing. Deep neural networks with massive learned knowledge. In EMNLP, 2016.

[23] Z. Hu, Z. Yang, X. Liang, R. Salakhutdinov, and E. P. Xing. Toward controlled generation of text. In ICMIL, 2017.

[24] Z. Hu, H. Shi, Z. Yang, B. Tan, T. Zhao, J. He, W. Wang, X. Yu, L. Qin, D. Wang, et al. Texar: A modularized, versatile, and extensible toolkit for text generation. arXiv preprint arXiv:1809.00794, 2018.

[25] Z. Hu, Z. Yang, R. Salakhutdinov, and E. P. Xing. On unifying deep generative models. In ICLR, 2018.

[26] T. Kim and Y. Bengio. Deep directed generative models with energy-based probability estimation. arXiv preprint arXiv:1606.03439, 2016.

[27] D. P. Kingma and M. Welling. Auto-encoding variational Bayes. arXiv preprint arXiv:1312.6114, 2013.

[28] M. J. Kusner, B. Paige, and J. M. Hernández-Lobato. Grammar variational autoencoder. arXiv preprint arXiv:1703.01925, 2017.

[29] H. Larochelle and I. Murray. The neural autoregressive distribution estimator. In AISTATS, 2011.

[30] S. Levine. Reinforcement learning and control as probabilistic inference: Tutorial and review. arXiv preprint arXiv:1805.00909, 2018.

[31] C. Li, J. Zhu, T. Shi, and B. Zhang. Max-margin deep generative models. In NIPS, pages 1837–1845, 2015.

[32] P. Liang, M. I. Jordan, and D. Klein. Learning from measurements in exponential families. In ICML, pages 641–648. ACM, 2009.

[33] X. Liang, Z. Hu, H. Zhang, C. Gan, and E. P. Xing. Recurrent topic-transition GAN for visual paragraph generation. In ICCV, 2017.

[34] X. Liang, Z. Hu, and E. Xing. Symbolic graph reasoning meets convolutions. In NIPS, 2018.

[35] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang. Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. In CVPR, pages 1096–1104, 2016.

[36] D. Lopez-Paz, L. Bottou, B. Schölkopf, and V. Vapnik. Unifying distillation and privileged information. arXiv preprint arXiv:1511.03643, 2015.

[37] L. Ma, X. Jia, Q. Sun, B. Schiele, T. Tuytelaars, and L. Van Gool. Pose guided person image generation. In NIPS, pages 405–415, 2017.

[38] L. Ma, Q. Sun, S. Georgoulis, L. Van Gool, B. Schiele, and M. Fritz. Disentangled person image generation. In CVPR, 2018.

[39] S. Mei, J. Zhu, and J. Zhu. Robust regBayes: Selectively incorporating first-order logic domain knowledge into bayesian models. In ICML, pages 253–261, 2014.

[40] S. Mohamed and B. Lakshminarayanan. Learning in implicit generative models. arXiv preprint arXiv:1610.03483, 2016.

[41] G. Neumann et al. Variational inference for policy search in changing situations. In ICML, pages 817–824, 2011.

[42] A. v. d. Oord, N. Kalchbrenner, and K. Kavukcuoglu. Pixel recurrent neural networks. arXiv preprint arXiv:1601.06759, 2016.

[43] J. Peters, K. Mülling, and Y. Altun. Relative entropy policy search. In AALI, pages 1607–1612. Atlanta, 2010.

[44] A. Pumarola, A. Agudo, A. Sanfeliu, and F. Moreno-Noguer. Unsupervised person image synthesis in arbitrary poses. In CVPR, 2018.

[45] J. Schulman, S. Levine, P. Abbeel, M. Jordan, and P. Moritz. Trust region policy optimization. In ICML, pages 1889–1897, 2015.

[46] J. Schulman, X. Chen, and P. Abbeel. Equivalence between policy gradients and soft Q-learning. arXiv preprint arXiv:1704.06440, 2017.
[47] R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*, volume 1. MIT press Cambridge, 1998.

[48] B. Tan, Z. Hu, Z. Yang, R. Salakhutdinov, and E. Xing. Connecting the dots between MLE and RL for text generation. 2018.

[49] B. Taskar, C. Guestrin, and D. Koller. Max-margin Markov networks. In *NIPS*, pages 25–32, 2004.

[50] D. Wang and Q. Liu. Learning to draw samples: With application to amortized MLE for generative adversarial learning. *arXiv preprint arXiv:1611.01722*, 2016.

[51] T.-C. Wang, M.-Y. Liu, J.-Y. Zhu, A. Tao, J. Kautz, and B. Catanzaro. High-resolution image synthesis and semantic manipulation with conditional GANs. *arXiv preprint arXiv:1711.11585*, 2017.

[52] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4):600–612, 2004.

[53] Z. Yang, Z. Hu, C. Dyer, E. Xing, and T. Berg-Kirkpatrick. Unsupervised text style transfer using language models as discriminators. In *NIPS*, 2018.

[54] S. Zhai, Y. Cheng, R. Feris, and Z. Zhang. Generative adversarial networks as variational training of energy based models. *arXiv preprint arXiv:1611.01799*, 2016.

[55] J. Zhao, M. Mathieu, and Y. LeCun. Energy-based generative adversarial network. *arXiv preprint arXiv:1609.03126*, 2016.

[56] B. D. Ziebart, A. L. Maas, J. A. Bagnell, and A. K. Dey. Maximum entropy inverse reinforcement learning. In *AAAI*, volume 8, pages 1433–1438. Chicago, IL, USA, 2008.

[57] G. Zweig and C. J. Burges. The Microsoft Research sentence completion challenge. Technical report, Citeseer, 2011.