Deep Generative Models with Learnable Knowledge Constraints

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Bridging the follows

- Posterior Regularization (PR)
- (forward) Reinforcement Learning (RL)
    - Entropy regularized policy optimization
- Inverse RL
    - Maximum entropy inverse RL

Mathematical Correspondence

Components	PR	Entropy-Reg RL	MaxEnt IRL	(Energy) GANs
$\mathbf{x}$	data/generations	action-state samples	demonstrations	data/generations
$p(\mathbf{x})$	generative model p_θ	(old) policy p_π	—	generator
$f(\mathbf{x})/R(\mathbf{x})$	constraint f_ϕ	reward R	reward R_ϕ	discriminator
$q(\mathbf{x})$	variational distr. q, Eq.3	(new) policy q_π	policy q_ϕ	—

Details in whiteboard

Algorithm

$$\begin{aligned}\nabla_\phi \mathbb{E}_{\mathbf{x}\sim p_d}\left[\log q(\mathbf{x})\right] &= \nabla_\phi \left[\mathbb{E}_{\mathbf{x}\sim p_d}\left[\alpha f_\phi(\mathbf{x})\right] - \log Z_\phi\right] \\ &= \mathbb{E}_{\mathbf{x}\sim p_d}\left[\alpha \nabla_\phi f_\phi(\mathbf{x})\right] - \mathbb{E}_{q(\mathbf{x})}\left[\alpha \nabla_\phi f_\phi(\mathbf{x})\right].\end{aligned} \tag{8}$$

$$\min_\theta \mathrm{KL}(q(\mathbf{x})\|p_\theta(\mathbf{x})) = \min_\theta -\mathbb{E}_{q(\mathbf{x})}\left[\log p_\theta(\mathbf{x})\right] + const. \tag{10}$$

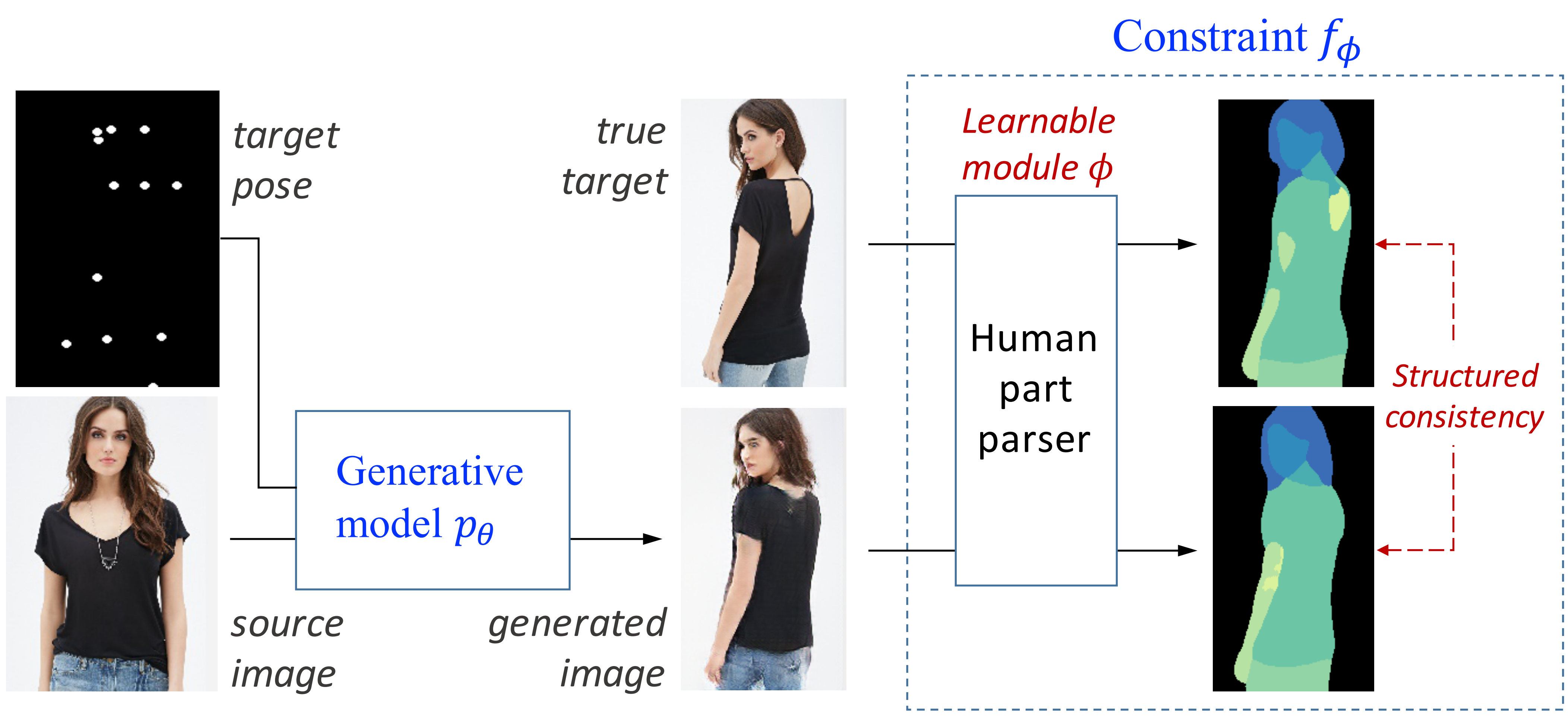
$$\nabla_\theta \mathrm{KL}\left(p_\theta(\mathbf{x})\|q(\mathbf{x})\right)|_{\theta=\theta^t} = -\nabla_\theta \mathbb{E}_{p_\theta}\left[\alpha f_{\phi^t}(\mathbf{x})\right]|_{\theta=\theta^t}. \tag{12}$$

Algorithm 1 Joint Learning of Deep Generative Model and Constraints

Input: The base generative model $p_\theta(\mathbf{x})$
The (set of) constraints $f_\phi(\mathbf{x})$
1: Initialize generative parameter $\boldsymbol{\theta}$ and constraint parameter $\boldsymbol{\phi}$
2: **repeat**
3: Optimize constraints $\boldsymbol{\phi}$ with Eq.(8)
4: **if** p_θ is an implicit model **then**
5: Optimize model $\boldsymbol{\theta}$ with Eq.(12) along with minimizing original model objective $\mathcal{L}(\boldsymbol{\theta})$
6: **else**
7: Optimize model $\boldsymbol{\theta}$ with Eq.(10) along with minimizing $\mathcal{L}(\boldsymbol{\theta})$
8: **end if**
9: **until** convergence
Output: Jointly learned generative model $p_{\theta^*}(\mathbf{x})$ and constraints $f_{\phi^*}(\mathbf{x})$

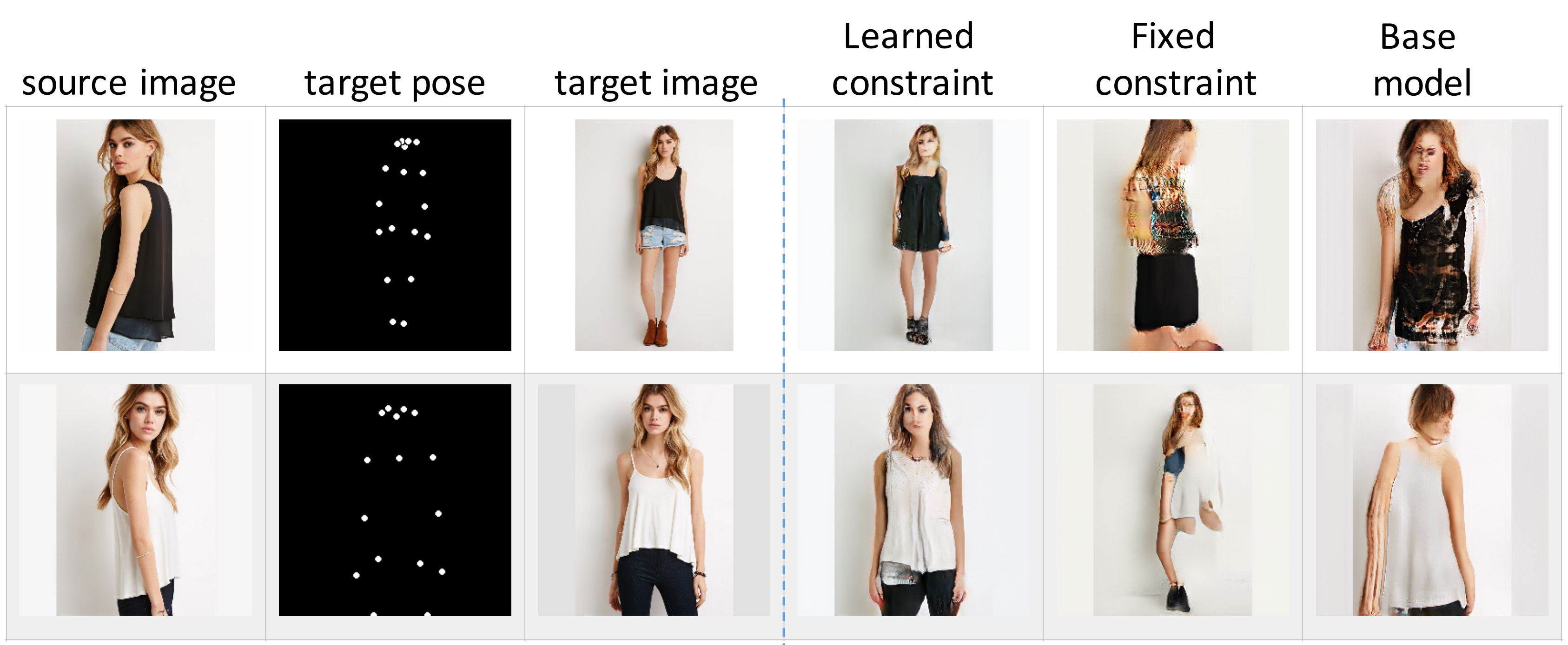
Experiments

- Pose Conditional Person Image Generation



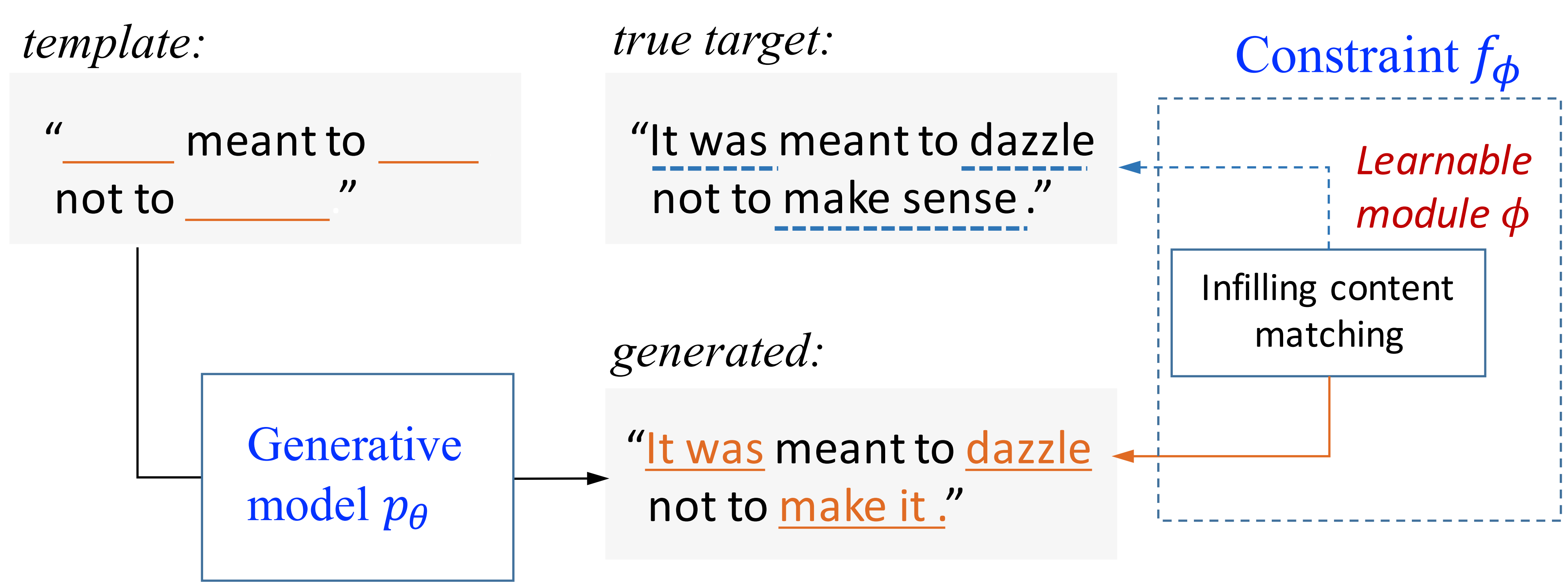
Results

	Method	SSIM	Human
1	Ma et al. (2018)	0.614	—
2	Pumarola et al. (2018)	0.747	—
3	Ma et al. (2017)	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**



Experiments

- Template guided Sentence Generation (**hit our interests**)



Results

	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 .

Discussions