TransGaGa: Geometry-Aware Unsupervised Image-to-Image Translation

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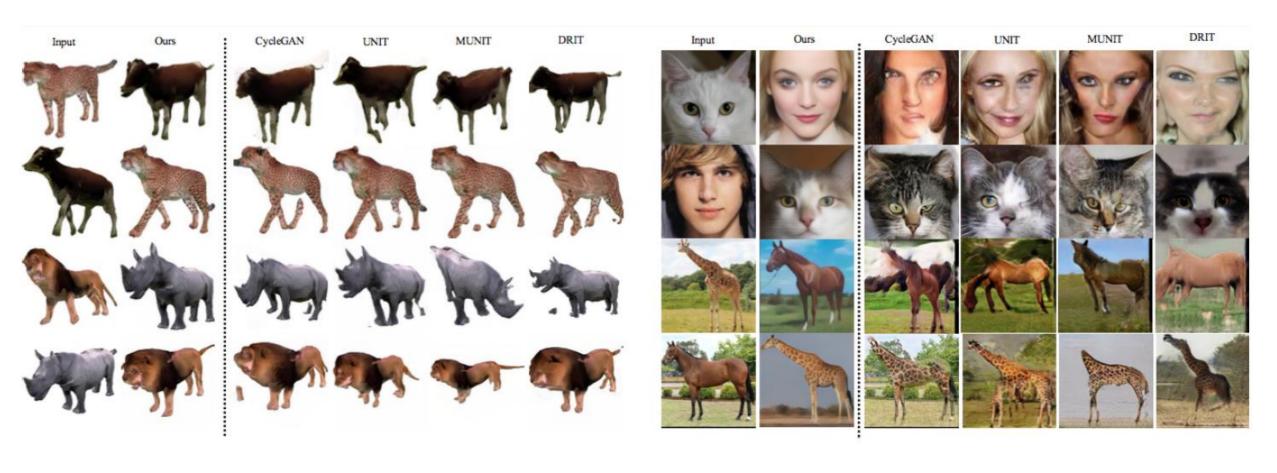
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19.06.25

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Motivation

- Learning a translation across <u>large geometry variations</u> always ends up with failure. So, They present a novel disentangle-and-translate framework to tackle the complex objects image-to-image translation task.

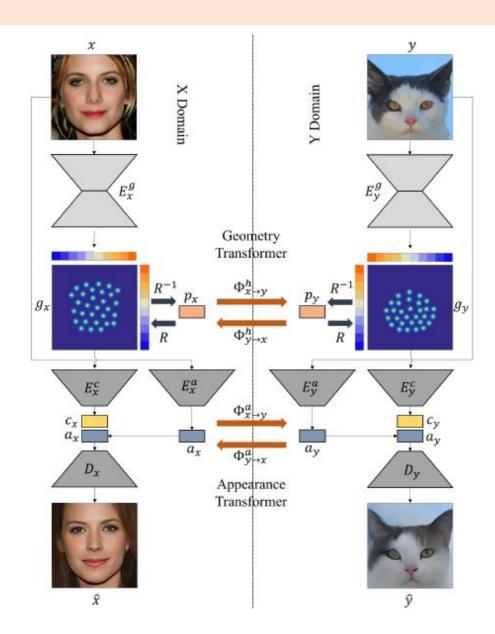


Contribution

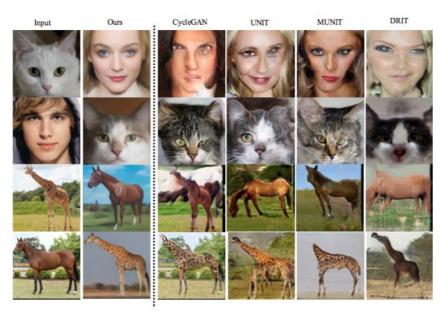
- They propose a <u>novel framework</u> for unsupervised image-to-image translation. Instead of directly translating on the image space, we build the mapping between two domains on their <u>disentangled latent appearance-geometry space</u>.

- <u>Fine-disentangled latent space</u> naturally endows our model with <u>the ability of diverse and exemplar-guided generation</u>, which is a <u>challenging and ill-posed multimodal problem</u> in unsupervised image-to-image translation.

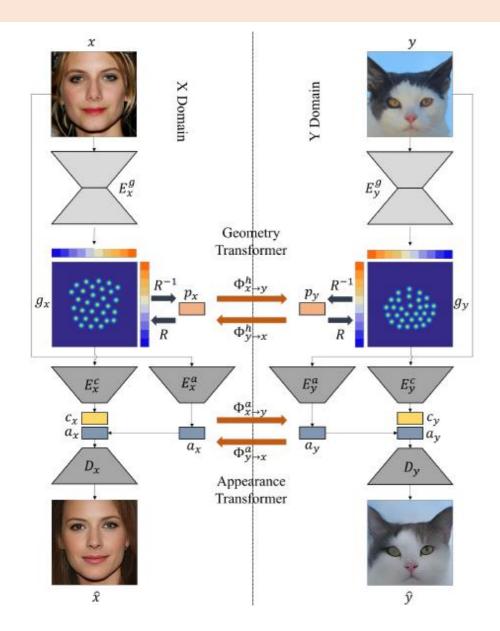
Method



- They assume each domain can be disentangled into a <u>Cartesian product of geometry(structure) space G and appearance space A.</u>
- Geometry 역할 : Spatial distribution이 다르더라도 같은 similar semantic meaning component끼리 mapping + 위치적 정보



Method



- Conditional VAE 사용

$$\mathcal{L}_{\text{disentangle}} = \mathcal{L}_{\text{CVAE}} + \mathcal{L}_{\text{prior}}$$

$$\mathcal{L}_{\text{CVAE}}(\pi, \theta, \phi, \omega) = -KL(q_{\phi}(c|x, g)||p(a|x))$$

$$+||x - D(E^{c}(E^{g}(x)), E^{a}(x))||,$$

Geometric map 의 supervision 없이 학습시키기 위해서 사용

$$\mathcal{L}\text{prior} = \sum_{i \neq j} \exp(-\frac{||g^i - g^j||^2}{2\sigma^2}) + \text{Var}(g)$$

- Transformer을 통한 mapping은 visual relationship 보장 X Cross-domain appearance consistency loss

$$\mathcal{L}_{\text{con}}^{a} = \|\zeta(x) - \zeta(D_{y}\left(\Phi_{x \to y}^{g} \cdot E_{x}^{g}(x), \Phi_{x \to y}^{a} \cdot E_{x}^{a}(x)\right))\|,\tag{4}$$

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CVAE}} + \mathcal{L}_{\text{prior}} + \mathcal{L}_{\text{con}}^{a} + \mathcal{L}_{\text{cyc}}^{a} + \mathcal{L}_{\text{cyc}}^{a} + \mathcal{L}_{\text{cyc}}^{g} + \mathcal{L}_{\text{cyc}}^{pix} + \mathcal{L}_{\text{adv}}^{a} + \mathcal{L}_{\text{adv}}^{g} + \mathcal{L}_{\text{adv}}^{pix}$$

Experiment

Table 1: **Human perceptual study.** Pairwise A/B tests on horse→giraffe and human→cat face task.

	horse \rightarrow giraffe	human $ ightarrow$ cat face		$\mathbf{horse} \to \mathbf{giraffe}$	human $ ightarrow$ cat face
Method	% Testers labeled <i>better</i>		Method	% Testers labeled <i>better</i>	% Testers labeled <i>better</i>
CycleGAN [52]	15.0%	15.4%	CycleGAN [52]	11.9%	25.7%
UNIT [27]	19.3%	18.9%	UNIT [27]	16.5%	23.3%
MUNIT [14]	20.4%	17.8%	MUNIT [14]	19.2%	31.7%
DRIT [23]	16.1%	23.4%	DRIT [23]	23.6%	34.4%
Ours	50.0 %	50.0%	Ours	50.0%	50.0%
	(-) a				

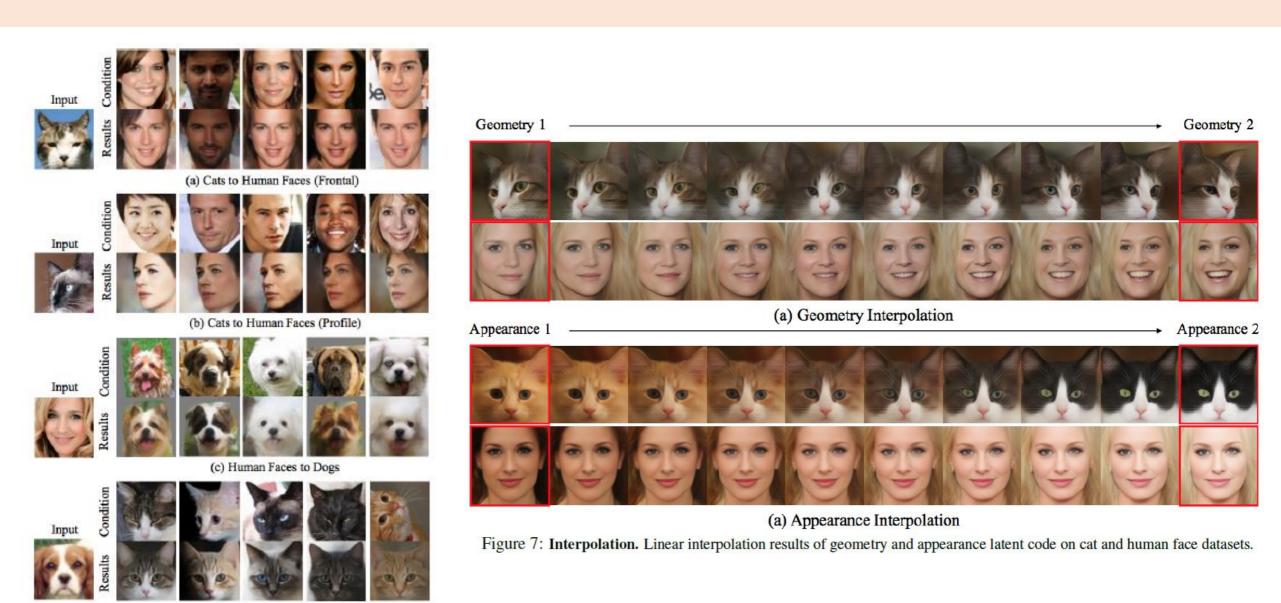
⁽a) Score of "realism". (b) Score of "geometry-consistency".

Table 2: **Quantitative Results.** We use FID (lower is better) and diversity (higher is better) with LPIPS distance to evaluate the quality and diversity of the generated images.

	Real Data		CycleGAN [52]		UNIT [27]		MUNIT [14]		DRIT [23]		Ours	
	FID	Diversity	FID	Diversity	FID	Diversity	FID	Diversity	FID	Diversity	FID	Diversity
$cats \rightarrow human face$	0.00	0.54	57.92	-	98.39	-	40.91	0.41	69.53	0.20	32.25	0.39
human face \rightarrow cats	0.00	0.65	44.23	-	35.26	-	23.24	0.53	33.14	0.52	21.88	0.56
$cats \rightarrow dogs$	0.00	0.66	143.14	-	104.32	-	100.26	0.59	67.01	0.54	65.77	0.60
$dogs \rightarrow cats$	0.00	0.65	75.75	-	66.84	-	27.60	0.56	31.04	0.59	23.23	0.58
$dogs \rightarrow human face$	0.00	0.54	105.09	-	103.35	-	37.84	0.40	46.70	0.32	31.06	0.41
human face \rightarrow dogs	0.00	0.66	149.61	-	91.38	-	73.98	0.60	68.84	0.57	52.20	0.67
Average	0.00	0.62	95.96	-	83.26	-	50.64	0.52	52.71	0.46	37.73	0.54

Experiment

(d) Dogs to Cats



Experiment

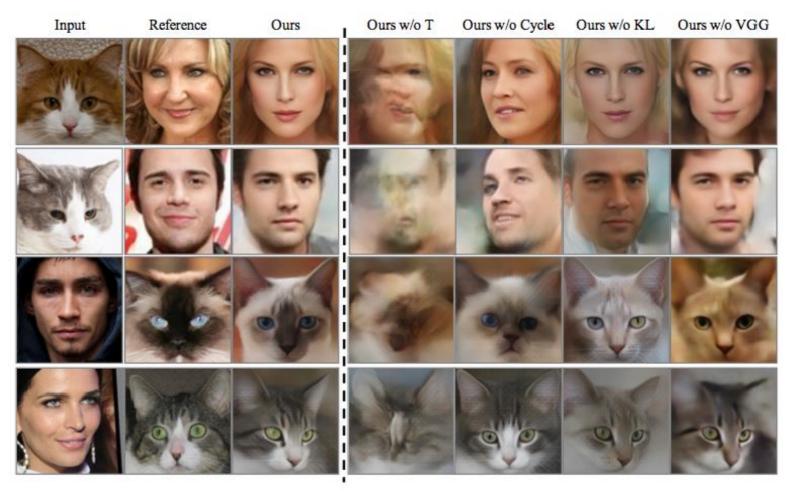


Figure 8: Quantitative ablation study. Visualisation results on human⇔cat task.