Weakly Supervised High-Fidelity Clothing Model Generation

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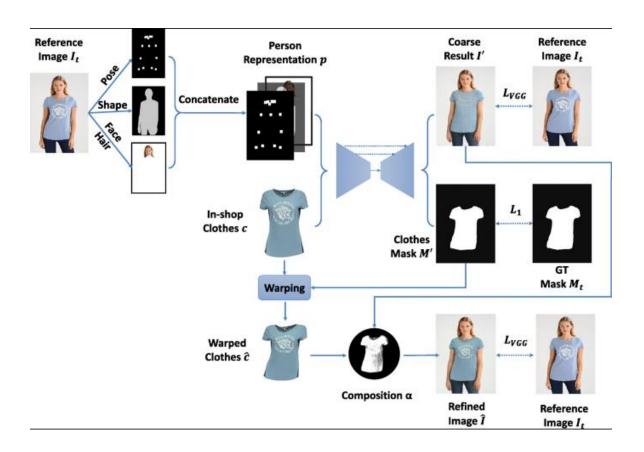
University of Science and Technology of China Zhejiang University Alibaba Group

CVPR 2022



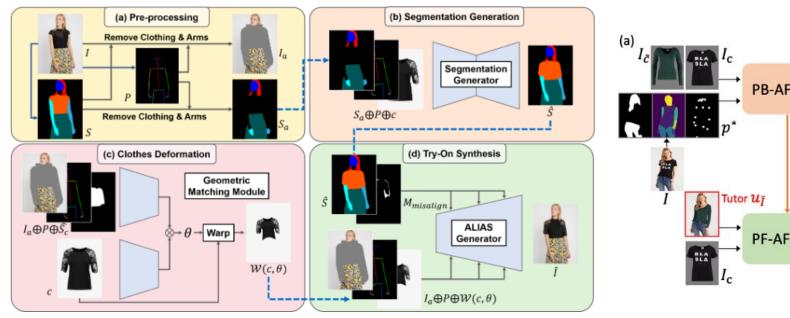
Virtual Try-on

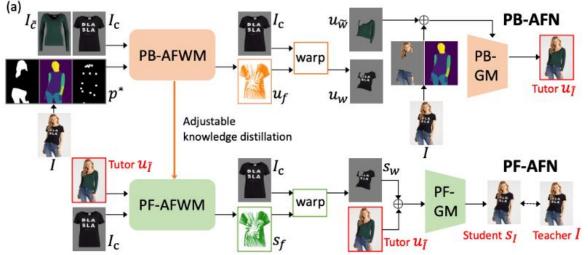




- VITON needs paired data
- Supervised learning

Virtual Try-on

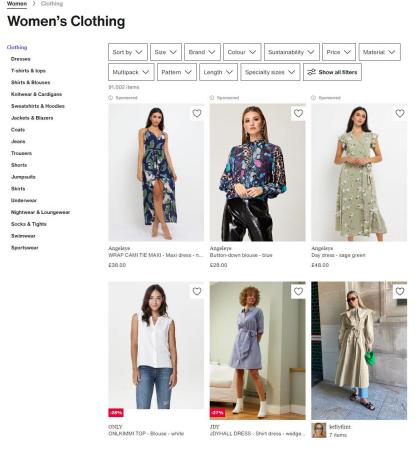




- "Parser-based" or "Parser-free"
- Warping + Synthesis

Motivation

- Proprietary model images are expensive!
- Training VITON model with large dataset -> high-fidelity
- Weakly supervised learning



Zalando website

Task setting

Conventional VITON setting

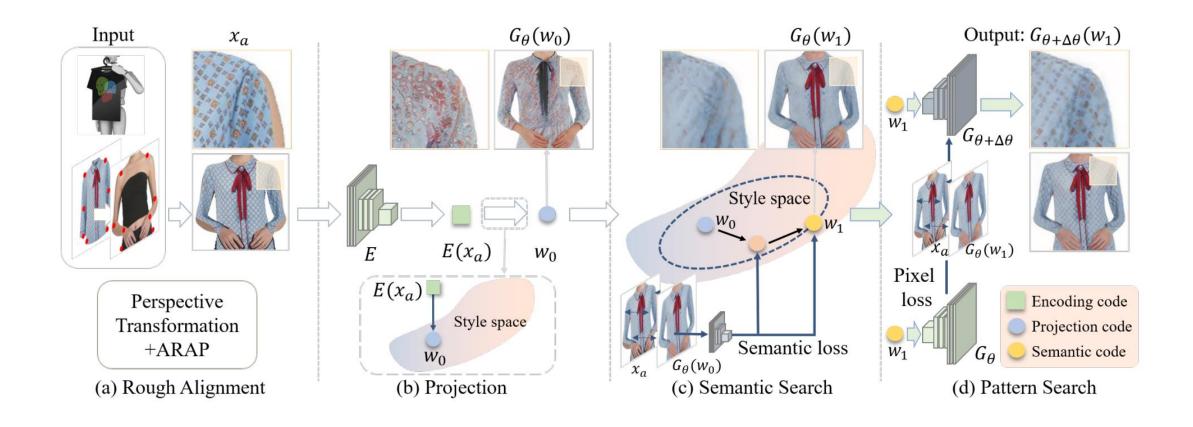


Proposed setting

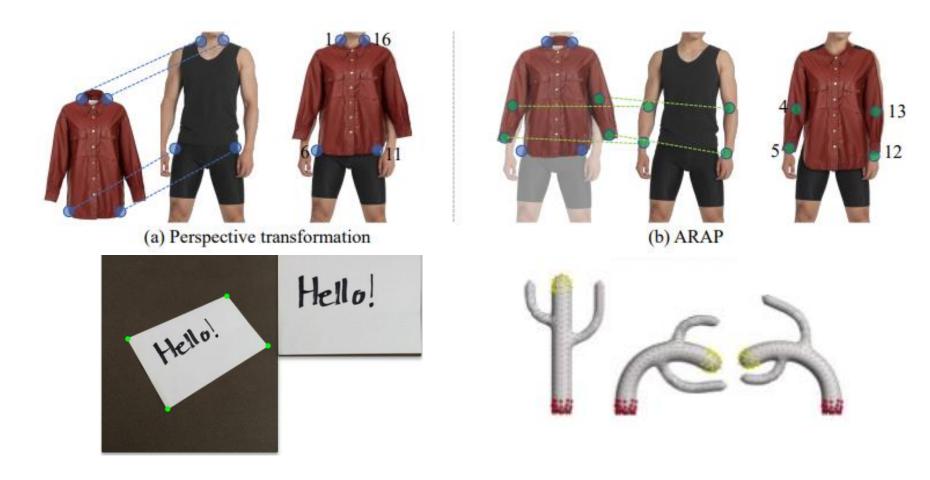


- The procedure of people predicting how they will look like while picking clothes
- Commercial Model Image dataset (CMI) 2,348 images of models on underwear or sleeveless

Overview

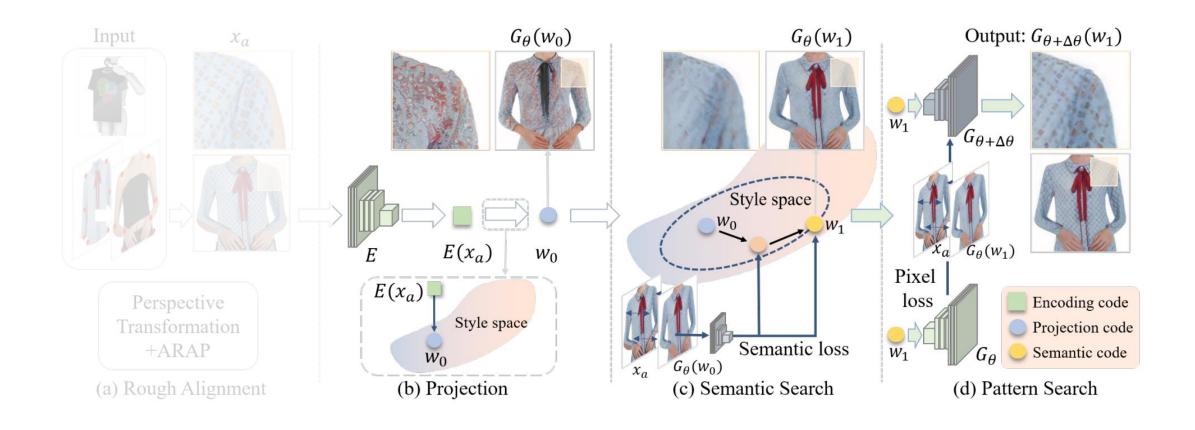


Rough Alignment



• Get a rough alignment image x_a

Deep Generative Projection

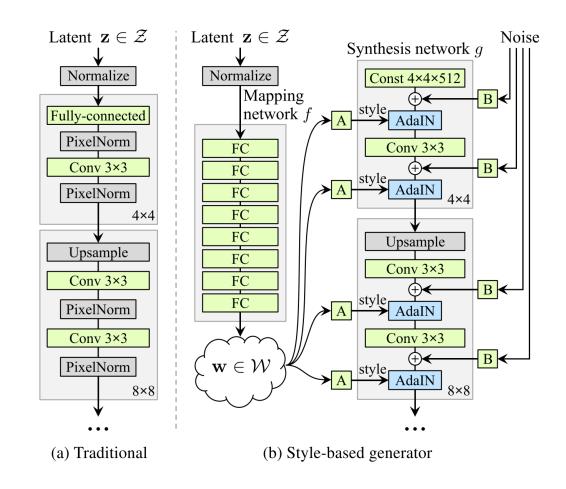




- Rough alignment -> Image with high-level semantics (clothing category, model pose)
- Refine flaw of the rough alignment

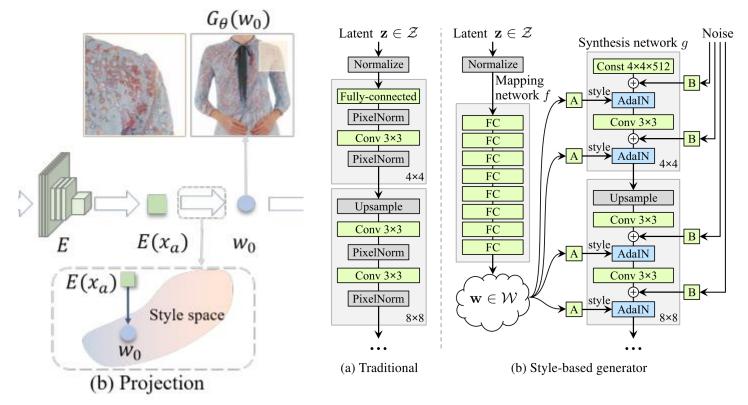
- Train pre-trained StyleGAN
- E-Shop Fashion(ESF) dataset
 - 180,000 clothing model images
 - 512 x 512
- FID 2.16





- Style space $\mathcal{W}+$
- Embedding images into high-density region of style space

-> To yield much more plausible synthesis



- Encoder \boldsymbol{E}
- 1. Compute PCA decomposition of 5M points on $\mathcal{W}+$
- 2. Get the mean value, covariance matrix, set of principal components

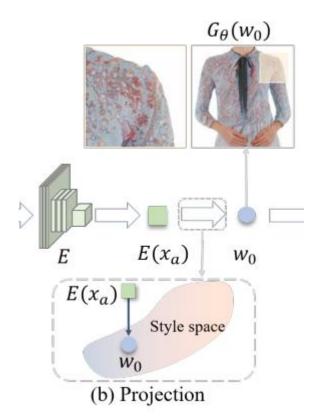
$$\mu$$
 Σ

$$Q = (q_1, ..., q_n)$$

3. Predicts series of principal strengths $s = (s_1, s_2, ..., s_n)^T$

$$egin{aligned} oldsymbol{s} &= oldsymbol{E}(oldsymbol{x}_a), \ oldsymbol{w}_0 &= Tr(oldsymbol{q}_1 s_1 \sqrt{\sigma_1} + ... oldsymbol{q}_n s_n \sqrt{\sigma_n}) + oldsymbol{\mu} & Tr(oldsymbol{v}) = \left\{ egin{aligned} oldsymbol{v}, \|oldsymbol{v}\|_2 < \psi, \ \frac{oldsymbol{v}}{\|oldsymbol{v}\|_2} \psi, \|oldsymbol{v}\|_2 \ge \psi. \end{aligned}
ight. \ &= oldsymbol{Q} oldsymbol{\Lambda}^{\frac{1}{2}} Tr(oldsymbol{s}) + oldsymbol{\mu}, \end{aligned}$$

$$\boldsymbol{w} = \boldsymbol{P}(\boldsymbol{x}_a)$$



Semantic search

Optimization problem

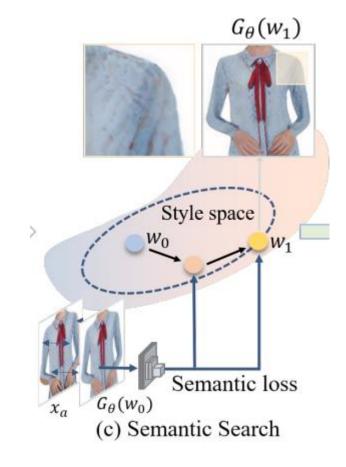
$$\min_{\boldsymbol{w} \in \mathcal{C}} \eta_p l_p + \eta_f l_f + \eta_{attr} l_{attr} + \eta_{adv} l_{adv},$$

$$l_p = \| \boldsymbol{W} * \boldsymbol{G}(\boldsymbol{w}) - \boldsymbol{W} * \boldsymbol{x}_a \|_2^2,$$

$$l_f = \| \boldsymbol{V}(\boldsymbol{W} * \boldsymbol{G}(\boldsymbol{w})) - \boldsymbol{V}(\boldsymbol{W} * \boldsymbol{x}_a) \|_2^2,$$

$$l_{attr} = \| \boldsymbol{R}(\boldsymbol{W} * \boldsymbol{G}(\boldsymbol{w})) - \boldsymbol{R}(\boldsymbol{W} * \boldsymbol{x}_a) \|_2^2,$$

$$l_{adv} = \log[1 - \boldsymbol{D}(\boldsymbol{G}(\boldsymbol{w}))],$$



Semantic search

Optimization problem

$$\min_{\boldsymbol{w} \in \mathcal{C}} \eta_p l_p + \eta_f l_f + \eta_{attr} l_{attr} + \eta_{adv} l_{adv},$$

$$l_p = \|W * \boldsymbol{G}(\boldsymbol{w}) - W * \boldsymbol{x}_a\|_2^2,$$

$$l_f = \|\boldsymbol{V}(W * \boldsymbol{G}(\boldsymbol{w})) - \boldsymbol{V}(W * \boldsymbol{x}_a)\|_2^2,$$

$$l_{attr} = \|\boldsymbol{R}(W * \boldsymbol{G}(\boldsymbol{w})) - \boldsymbol{R}(W * \boldsymbol{x}_a)\|_2^2,$$

$$l_{adv} = \log[1 - \boldsymbol{D}(\boldsymbol{G}(\boldsymbol{w}))],$$



Rough Alignment

Projection

$$W_{ij} = \begin{cases} 1 - \exp(-d((i,j), \partial I)^2), & I(ij) = 1, \\ 0, & I(ij) = 0. \end{cases}$$

Semantic search

Optimization problem

$$\min_{\boldsymbol{w} \in \mathcal{C}} \eta_p l_p + \eta_f l_f + \eta_{attr} l_{attr} + \eta_{adv} l_{adv},$$

$$l_p = \|W * \boldsymbol{G}(\boldsymbol{w}) - W * \boldsymbol{x}_a\|_2^2,$$

$$l_f = \|\boldsymbol{V}(W * \boldsymbol{G}(\boldsymbol{w})) - \boldsymbol{V}(W * \boldsymbol{x}_a)\|_2^2,$$

$$l_{attr} = \|\boldsymbol{R}(W * \boldsymbol{G}(\boldsymbol{w})) - \boldsymbol{R}(W * \boldsymbol{x}_a)\|_2^2,$$

$$l_{adv} = \log[1 - \boldsymbol{D}(\boldsymbol{G}(\boldsymbol{w}))],$$

• Constrain C

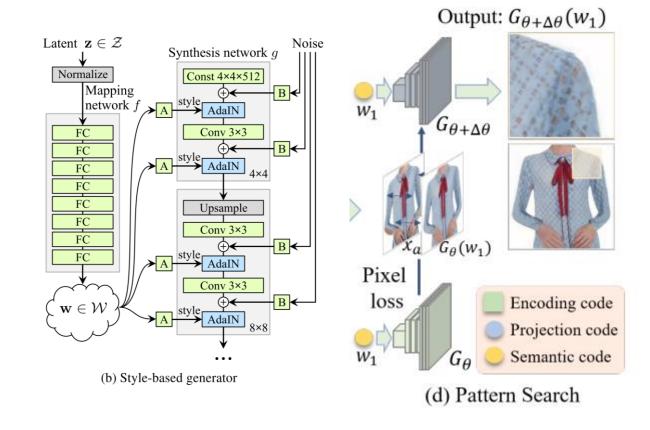
$$\mathbf{w}_{k+1} = \arg\min_{\mathbf{w} \in \mathcal{C}} \|\mathbf{w}_{k+1} - \mathbf{w}\|$$

$$= \begin{cases} \mathbf{w}_0 + 4 \frac{\mathbf{w}_{k+1} - \mathbf{w}}{\|\mathbf{w}_{k+1} - \mathbf{w}\|_2}, & \|\mathbf{w}_{k+1} - \mathbf{w}_m\|_2 > 4, \\ \mathbf{w}_{k+1}, & \|\mathbf{w}_{k+1} - \mathbf{w}\|_2 \le 4. \end{cases}$$

Pattern search

Optimization problem

$$\min_{\boldsymbol{\theta} \in B(\boldsymbol{\theta}_0, 4)} \eta_p \| W * \boldsymbol{G}_{\boldsymbol{\theta}}(\boldsymbol{w}) - W * \boldsymbol{x}_a \|_2$$
$$+ \log(1 - \boldsymbol{D}(\boldsymbol{G}_{\boldsymbol{\theta}}(\boldsymbol{w}))),$$



Experiments

Table 1. Numerical metrics of DGP, ACGPN, PF-AFN, and VITON-HD on CMI and MPV datasets. ↓ indicates lower is better.

Methods	CMI		MPV	
	FID↓	SWD↓	FID↓	SWD↓
ACGPN	137.9	121.3	81.1	90.4
PF-AFN	97.3	76.7	67.8	67.1
VITON-HD	87.5	56.1	40.6	52.7
DGP (Ours)	51.6	22.4	48.4	36.7

Experiments



Figure 8. Comparison on the CMI and MPV datasets. The supervised competitor methods are basically less appealing, and perform especially poorly on complicated clothing like coats.

Experiments



Figure S10. More visual results of qualitative comparison on the CMI dataset.