

Pluralistic Image Completion

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 $\mathcal{N}_m(\mathbf{0}, \sigma^{2(i)}(n)\mathbf{I})$

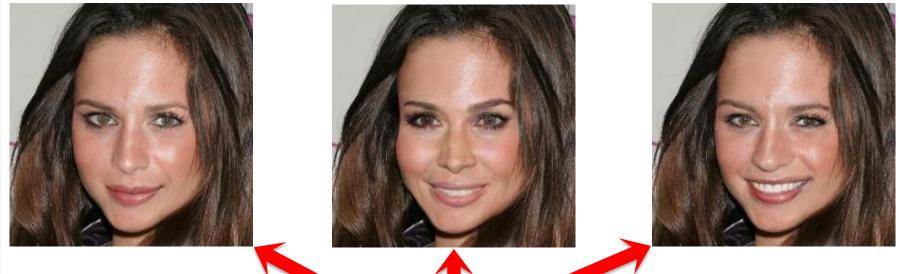
Self-Attention

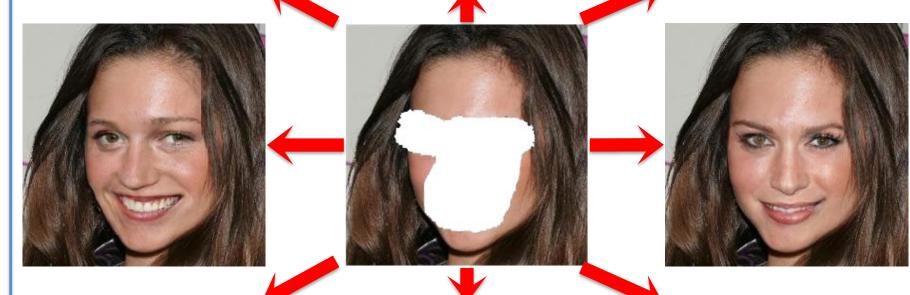


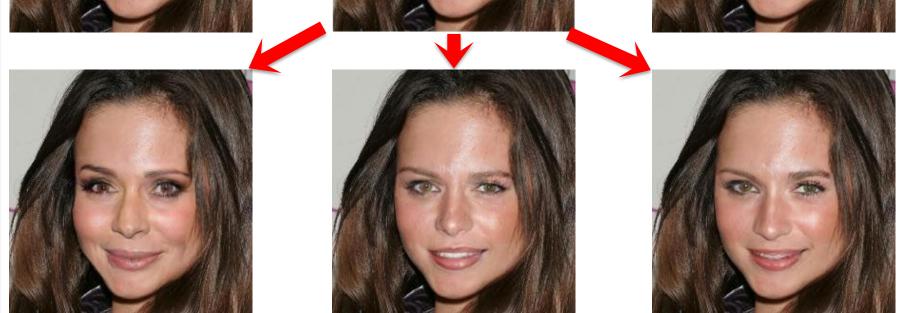
LONG BEACH CALIFORNIA June 16-20, 2019

Motivation

What would you imagine to be filled?





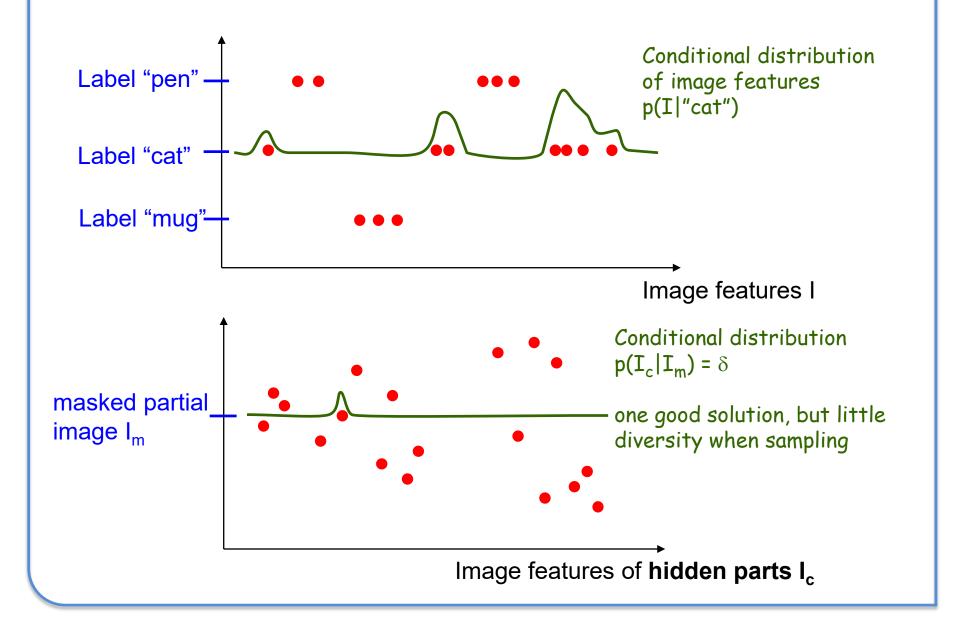


Problem:

- 1. Only one "optimal" result is typically generated in existing image completion work
- 2. Most methods focus on reconstructing the original image during the training.

Goal: multiple and diverse plausible results

Challenge: only one "ground truth" is available during the training



Key Ideas

- 1. A probabilistically principled framework
 - > Assume missing partial images (patches) belong to a prior distribution

 $\log p(\mathbf{I}_c) \ge -\mathrm{KL}(q_{\psi}(\mathbf{z}_c|\mathbf{I}_c)||p(\mathbf{z}_c)) + \mathbb{E}_{q_{\psi}(\mathbf{z}_c|\mathbf{I}_c)}[\log p_{\theta}(\mathbf{I}_c|\mathbf{z}_c)] \blacksquare$

Couple prior-conditional lower bound

 $\log p(\mathbf{I}_c|\mathbf{I}_m) \ge - \mathrm{KL}(q_{\psi}(\mathbf{z}_c|\mathbf{I}_c)||p_{\phi}(\mathbf{z}_c|\mathbf{I}_m))$ $\mathbb{E}_{q_{\psi}(\mathbf{z}_c|\mathbf{I}_c)}[\log p_{ heta}(\mathbf{I}_c|\mathbf{z}_c,\mathbf{I}_m)]$

Reconstruction vs Creative Generation

 $\log p(\mathbf{I}_c|\mathbf{I}_m) \ge \lambda \left\{ \mathbb{E}_{q_{\psi}}[\log p_{\theta}^r(\mathbf{I}_c|\mathbf{z}_c,\mathbf{I}_m)] - \mathrm{KL}(q_{\psi}||p_{\phi}) \right\}$ $+ (1 - \lambda) \mathbb{E}_{p_{\phi}} [\log p_{\theta}^{g}(\mathbf{I}_{c}|\mathbf{z}_{c},\mathbf{I}_{m})]$

Joint unconditional and conditional lower bounds $\mathcal{B} = \beta \, \mathcal{B}_1 + \mathcal{B}_2$

> $= - \left[\beta KL(q_{\psi}||p_{z_c}) + \lambda KL(q_{\psi}||p_{\phi}) \right]$ $+ (\beta + \lambda) \mathbb{E}_{q_{\psi}} \log p_{\theta}^{r} + (1 - \lambda) \mathbb{E}_{p_{\phi}} \log p_{\theta}^{g}$

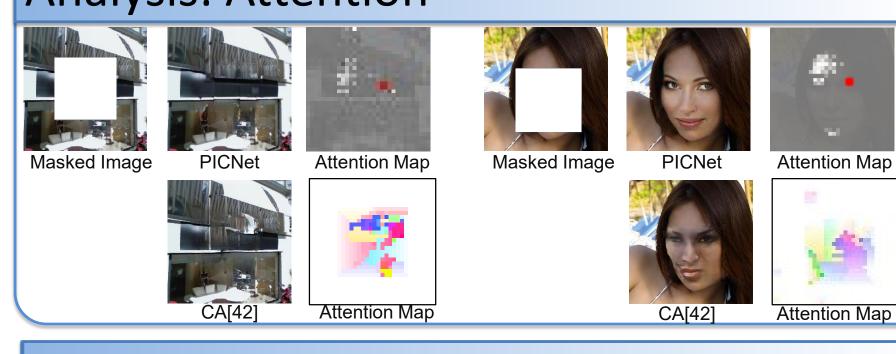
2. A novel self-attention layer to exploit short + long term context information

Attend to the finer-grained features in the encoder or the more semantically generative features in the decoder

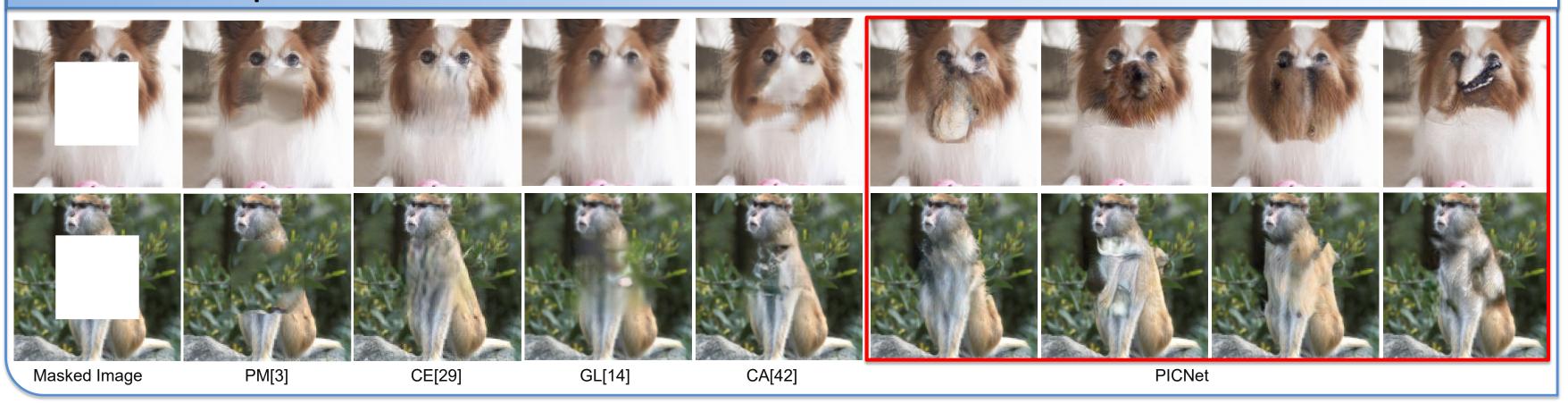
$N_{\psi}(\mathbf{u}^{(i)}, oldsymbol{\sigma}^{2(i)}\mathbf{I})^{5}$ Inf2 $\mathcal{N}_{\phi}(\mathbf{u}^{(i)}, \boldsymbol{\sigma}^{2(i)}\mathbf{I})$ **Short + Long Term Attention** Attention Maps

Pluralistic Image Completion Network (PICNet)





Overall Comparison with Other Methods

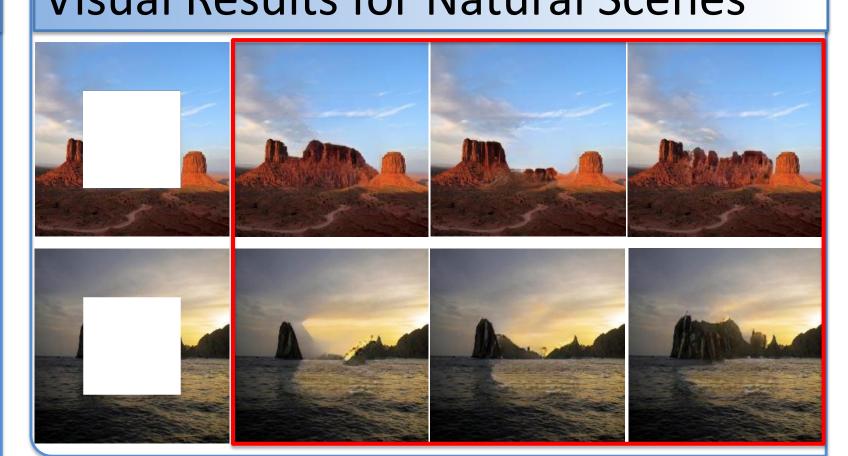


Deco der Feature

Visual Results for Buildings



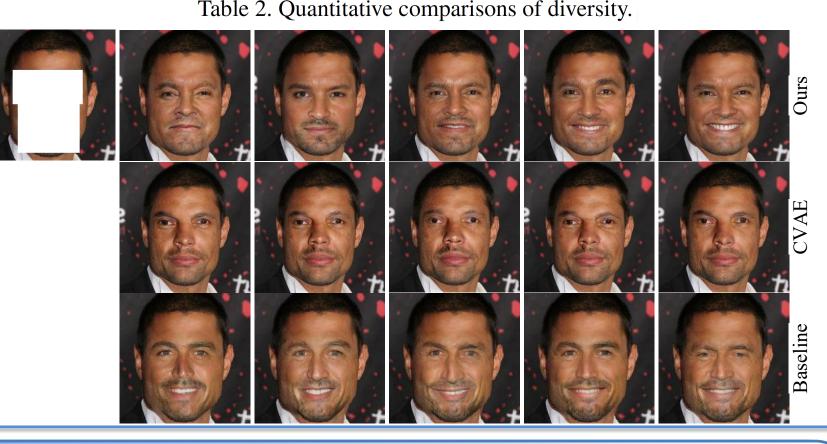
Visual Results for Natural Scenes



Analysis: Diversity

	Diversity (LPIPS)	
Method	\mathbf{I}_{out}	$\mathbf{I}_{out(m)}$
CVAE	0.004	0.014
Instance Blind	0.015	0.049
BicycleGAN [46]	0.027	0.060
PICNet-Pluralistic	0.029	0.088

Table 2. Quantitative comparisons of diversity.



More Source: Project and Code

