





Bridging Global Context Interactions for High-Fidelity Image Completion

Chuanxia Zheng¹, Tat-Jen Cham², Jianfei Cai¹, Dinh Phung¹

Tfill-Coarse: Global Content Inference

Restrictive CNN: embed patch visible context

Weighted Self-Attention Layer: bias visible token

CNN-based Decoder: generate tokens in parallel

¹Department of Data Science & AI, Monash University ²School of Computer Science and Engineering, NTU

Tfill-Refined: Global Appearance Refinement

AAL: copy global

context from both

decoded features

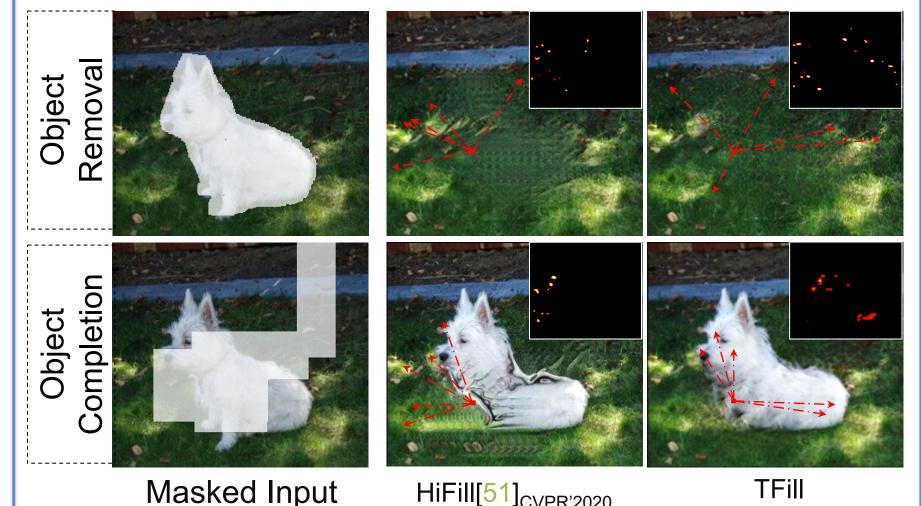
encoded and

Motivation

Goal: semantic image completion, not purely for removing objects

Challenge:

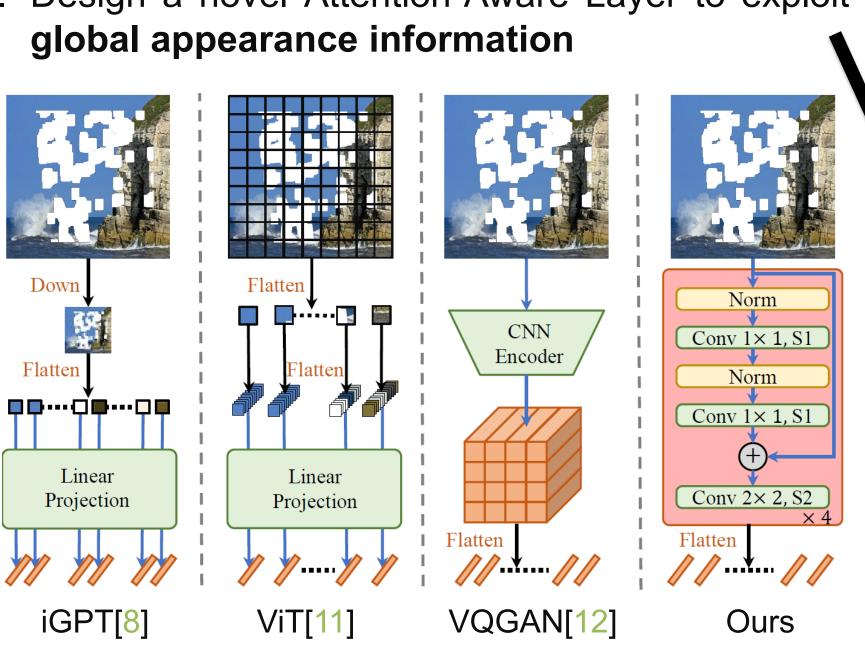
- 1. CNN gradually affected by neighboring pixels
- 2. Pixel-level attention requires *expensive* costs



How to correctly model the disconnected context?

Key Insights

- 1. Propose a transformer-based framework with the restrictive CNN to correctly model the global content in each attention layer
- 2. Design a novel Attention-Aware Layer to exploit



Pipeline: Two-stage Image Completion Masked input Coarse output (256²) Transformer Encoder MLP Norm Restrictive CNN Up and Recompose Multi-head Attention **CNN Networks** Novel Layers Norm Transformer Layers Embedded Tokens Original ground truth Recomposed input Refined output

Analysis: Architecture of TFill

Method	CelebA-HQ		FFHQ	
	LPIPS↓	FID↓	LPIPS↓	FID↓
CA [52] _{CVPR'2018}	0.104	9.53	0.127	8.78
PIC [60] _{CVPR'2019}	0.061	6.43	0.068	4.61
MEDFE [29] _{ECCV'2020}	0.067	7.01	-	-
A Traditional Conv	0.060	6.29	0.066	$\bar{4}.\bar{1}2$
	0.059	6.34	0.064	4.01
\mathbb{C} + Restrictive <i>Conv</i>	0.056	4.68	0.060	3.87
	0.051	4.02	0.057	3.66
	0.050	3.92	0.057	3.63
F + Refine Network	0.048	3.86	0.053	3.50

















Analysis: Attention-Aware Layer

