#### Is it REAL? Challenges in Image Synthesis

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# Is it REAL?



# **Does it Look REAL?**

[Gatys, et al. CVPR 2016]



# **Does it Look REAL?**

[Mechrez, et al. BMVC 2017]



# **Does it Feel REAL?**

· En



### **Touch and Feel**



Communications



Pushing the boundaries of CNNs

#### **GENERATING IMAGES THAT LOOK REAL**



#### Style Transfer as a Case Study





#### Single-Image Super-Resolution





#### Style Transfer as a Case Study





#### Solution with CNNs

#### It's all in the loss!!





input

target

loss







#### The current loss functions

#### Pixel-to-pixel

*L1, L2, Perceptual, ....* **Require alignment !!** 





input

target







#### The current loss functions





#### <u>Global style</u>

Gram

Global statistics !!

input

target

loss



Gram loss output





#### Wrong Semantics



target

loss

#### <u>Global style</u>

Gram

Global statistics !!

input



Gram loss output



# Compare regions based on semantics (and NOT spatial position)



Generated image

target



#### The Contextual loss





#### **A Statistical Measure**





#### similar distributions

different distributions













Input

Style

Mr. Beanary





Input

Style







Input

Style

Mr. Beanama





Input

Style

Barack De Níro





Input

Style

#### Hillabama

# **Does it Look REAL?**





# Does it Look REAL?

















Input

Style

Output

Does it Look REAL?













Input

Does it Look REAL?





Style



CNNMRF



Output





#### **Gender Change**



Architecture: CRN





#### Male-to-Female



## **Does it Look REAL?**



#### Female-to-Male



# **Does it Look REAL?**



#### Male-to-Female



#### Female-to-Male



Pushing the boundaries of CNNs

#### **GENERATING IMAGES THAT LOOK REAL**



#### Artifacts

Stylized



# [Gatys, et al. CVPR 2016]

#### **More Realistic**

1 91.07





#### Statistics of Natural Images



Communications

#### Statistics of Natural Images



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#### A Statistical Measure



#### similar distributions

different distributions





#### Single-Image Super-Resolution



#### **Typical Input**





#### **Typical Result**





#### **Internal Image Statistics**

#### Random projections of image patches



#### Minimizing the KL-divergence





#### Bicubic





#### Glasner et. al.



[Glasner , Bagon and Irani. Super-Resolution From a Single Image. ICCV 2009]



#### SRGAN



[Ledig et al. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. CVPR 2017]



#### Proposed



 $\mathcal{L}_{CX}$ 



#### Ground Truth HD





#### **Perceptual Super-Resolution**







#### **Power Spectrum**



Computers

#### Quantitative

Indice	Johnson et al. [16]	SRGAN [5]	EnhanceNet [20]	ours
Distortion: SSIM	0.631	0.640	0.624	0.643
Perceptual: Ma et al. [22]	7.800	8.705	8.719	8.800





Communications



**L1** 



GT



**L1** 



GT

"Facts are stubborn things, but statistics are pliable." Mark Twain



#### **THANK YOU**

