

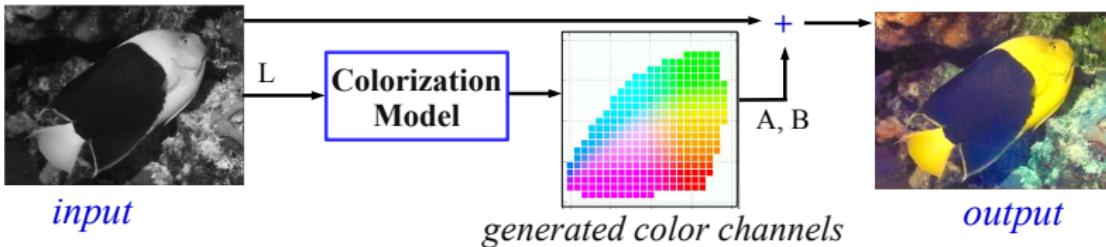
Automatic Image Colorization using Generative Adversarial Networks

Team: Yet Another Layer - YAL

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Image Colorization

Problem: produce a *realistic* coloring of gray-scale images



Applications



Colorizing old photos and movies



Colorizing underwater images

Figure sources: [1], [2], [3]

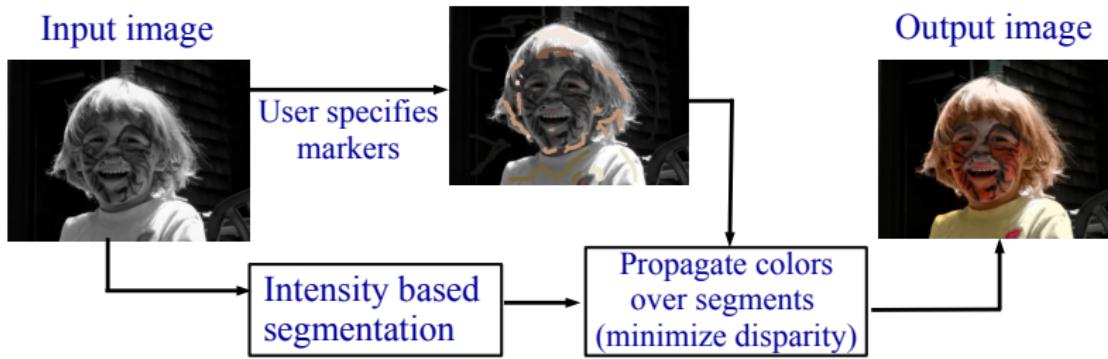


Background

- Algorithmic choices:
 - **Image-to-image translation**
 - Classification
- Colorspace choices:
 - **LAB**, RGB
- Approaches
 - Classical
 - Deep learning based
 - Generative models
 - **Adversarial model**

Classical Approaches

Colorization using User-specified Prior [4]



Pros

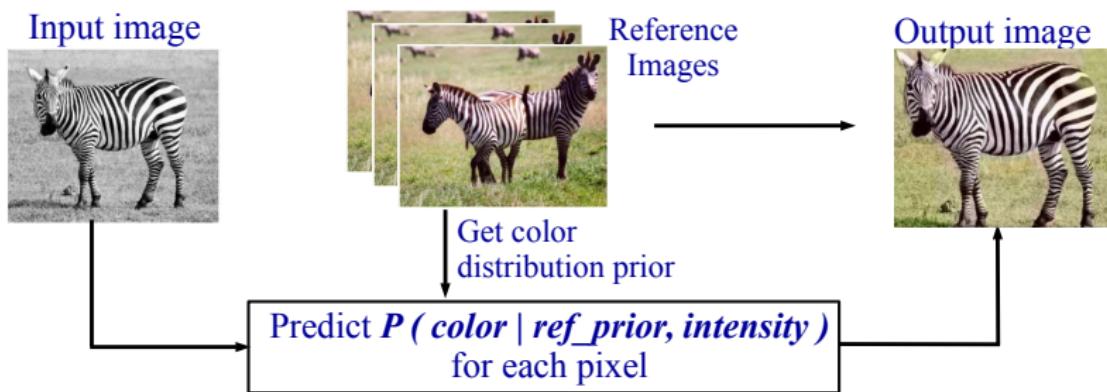
Fast
Reliable

Cons

Not automatic
Not scalable

Classical Approaches

Colorization using Multi-modal Prediction [5]



Pros

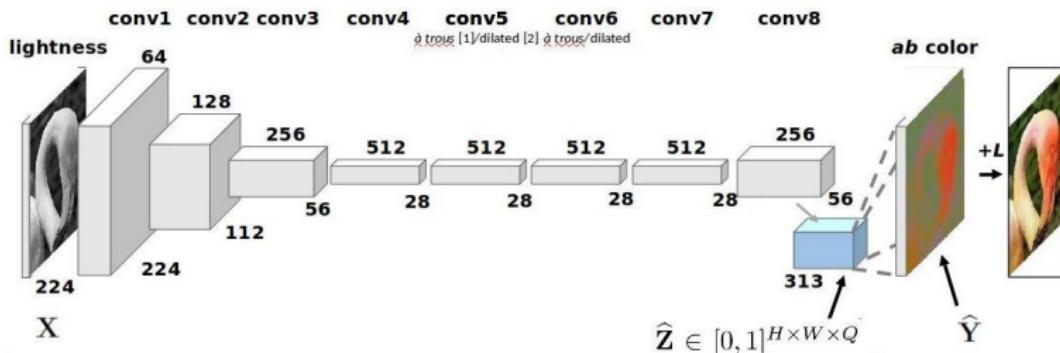
Automatic
Handles multimodality

Cons

Depends heavily on reference prior
Not practical

Generative Approach

Colorful Image Colorization model [1]



Model Changes	Original model	Adopted model
Output	Classification Probabilities	Image
Trained on	ImageNet	CelebA, Places2
Implementation	Caffe	Tensor-flow

Results

Colorful Image Colorization model as generator only

True Input Output



True Input Output



CelebA dataset

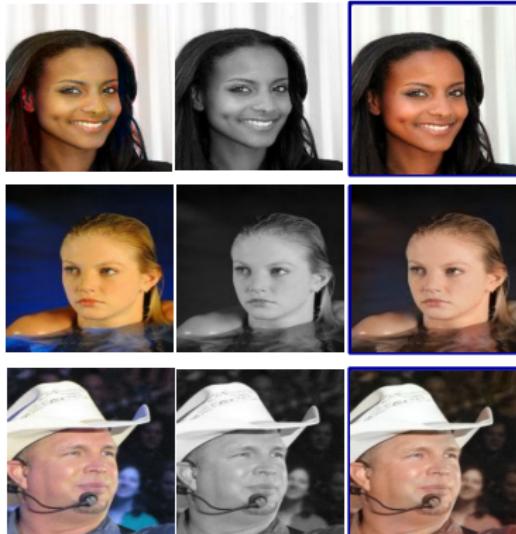
Places2 dataset

Loss functions: **L1 loss**, L2 loss, Least-squared loss

Results

Colorful Image Colorization model as generator in a GAN

True Input Output

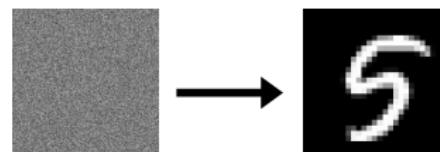


True Input Output



Generative Adversarial Networks (GANs)

- Two player minimax game
 - Discriminator **D**
 - Generator **G**
- D is trained to discriminate between a real image and a generated image
- G is trained to generate an image that will fool D
- Both G and D are neural networks



$$\min_G \max_D \mathbb{E}_{x \sim p_{data(x)}} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

- Conditional GANs generate images given conditional information, such as a class label.

GAN Variations

- Deep Convolutional GANs (DCGANs)
 - Bridge the gap between GANs and Deep Learning
- Least Squares GANs (LSGANs)
 - Use a least squares loss for the discriminator
- Energy-Based GANs (EBGANs)
 - Model the discriminator as an energy function
- Wasserstein GAN (WGAN)
 - Minimizes the Earth Mover distance between two distributions

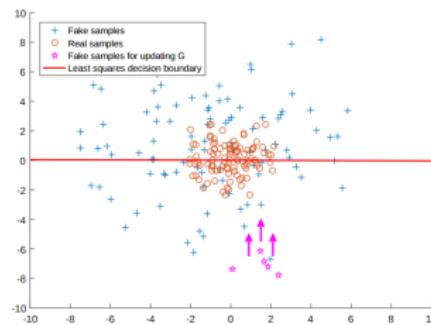


Fig. source: [7]

GAN Comparison Results

MNIST

GAN, DCGAN

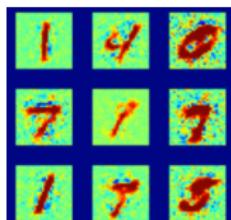
CelebA

EBGAN, WGAN

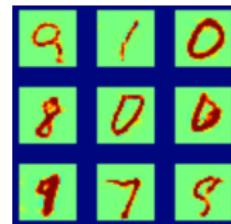
LSUN

LSGAN

GAN



DCGAN



EBGAN



LSGAN

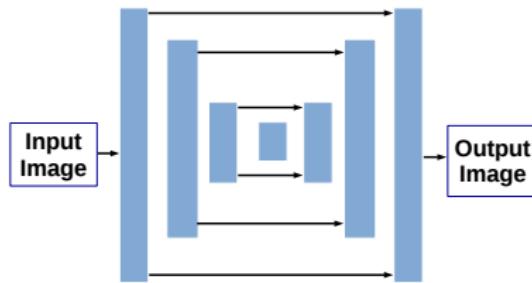


WGAN

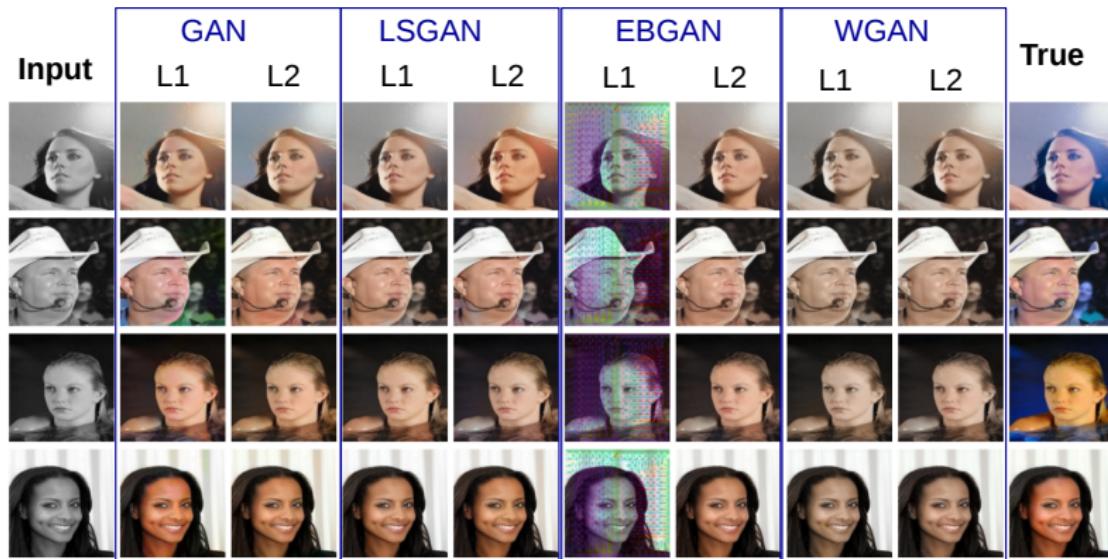


GANs Towards Colorization

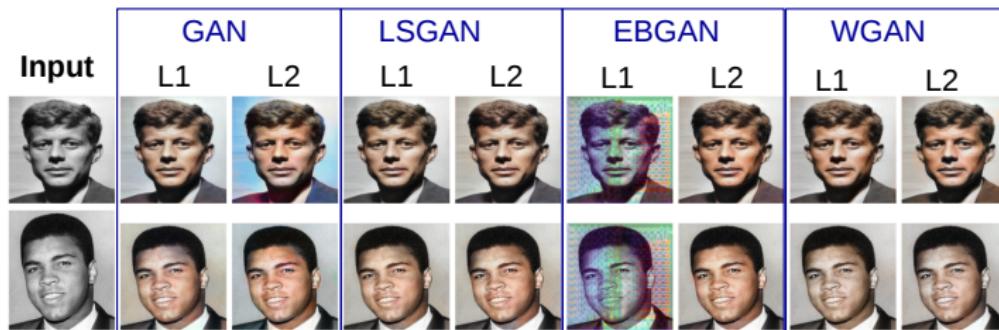
- Tested two generators
 - Pix2Pix
 - Colorful Image Colorization
- Pix2Pix generator is modeled as an encoder-decoder with skip connections
- Combine L1 and L2 loss with GAN Variations



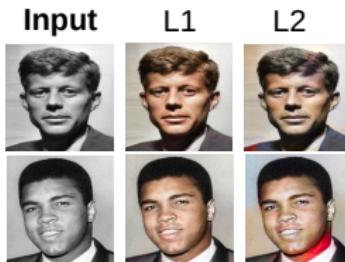
Results in Comparison



Legacy Grayscale Results



Pic2Pix model as Generator



Colorful Image Colorization model as Generator

Lessons Learned

- Automatic colorization is difficult due to
 - Ambiguity
 - Multi-modality
- Need large datasets to *learn* colorization
- GANs are tricky
- Long turnover time, at least 1 to 2 days
- End to end trainable
- Inference is 30fps on CPU, 60fps on GPU

References

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- 7 Mao, Xudong, et al. *Least squares generative adversarial networks*. arXiv preprint ArXiv:1611.04076 (2016).
- 8 Arjovsky, Martin, Soumith Chintala, and Lon Bottou. *Wasserstein gan*. arXiv preprint arXiv:1701.07875 (2017).
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- 10 Radford, Alec, Luke Metz, and Soumith Chintala. *Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks*. ICLR (2016): <https://arxiv.org/abs/1511.06434>.