

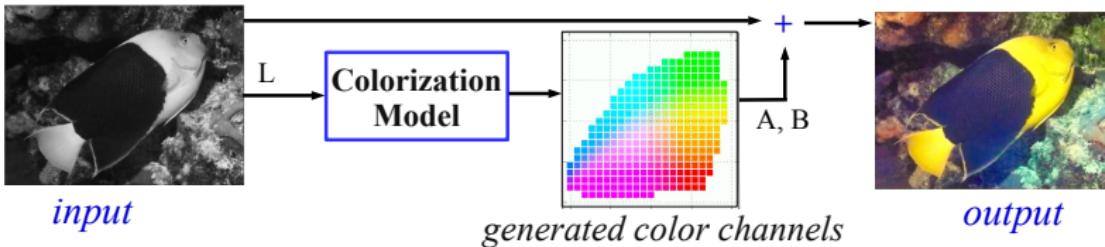
# Automatic Image Colorization using Generative Adversarial Networks

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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]

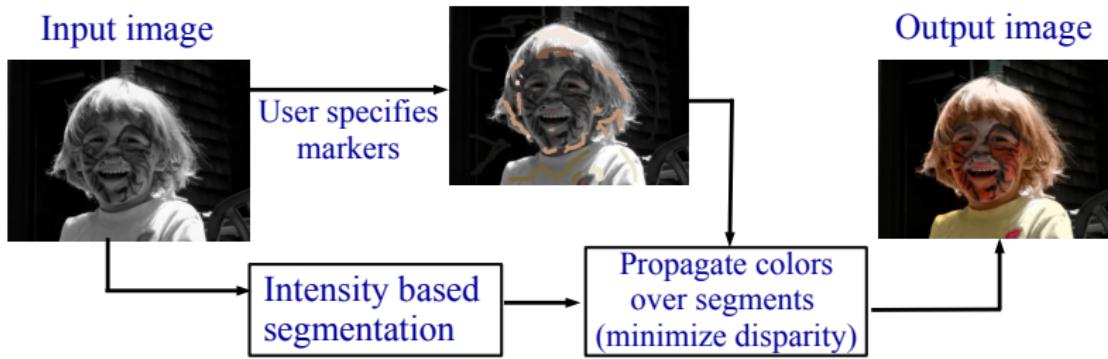


# Background

- 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

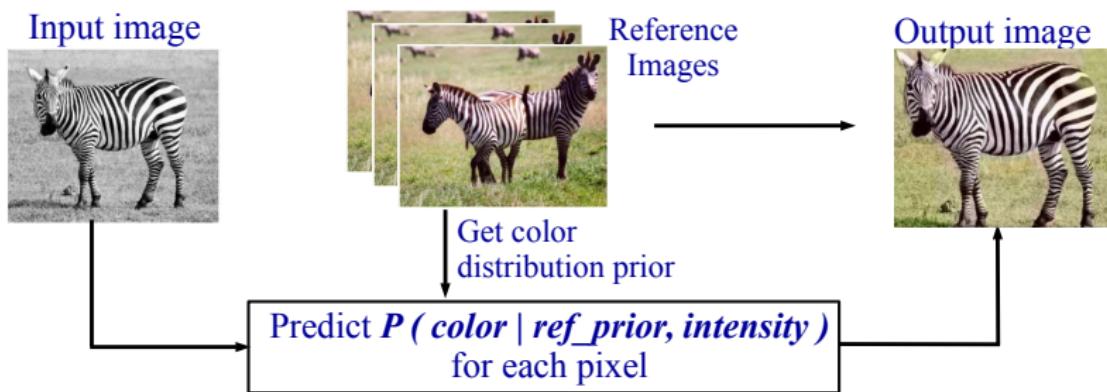
Fast  
Reliable

### Cons

Not automatic  
Not scalable

# Classical Approaches

## Colorization using Multi-modal Prediction [5]



### Pros

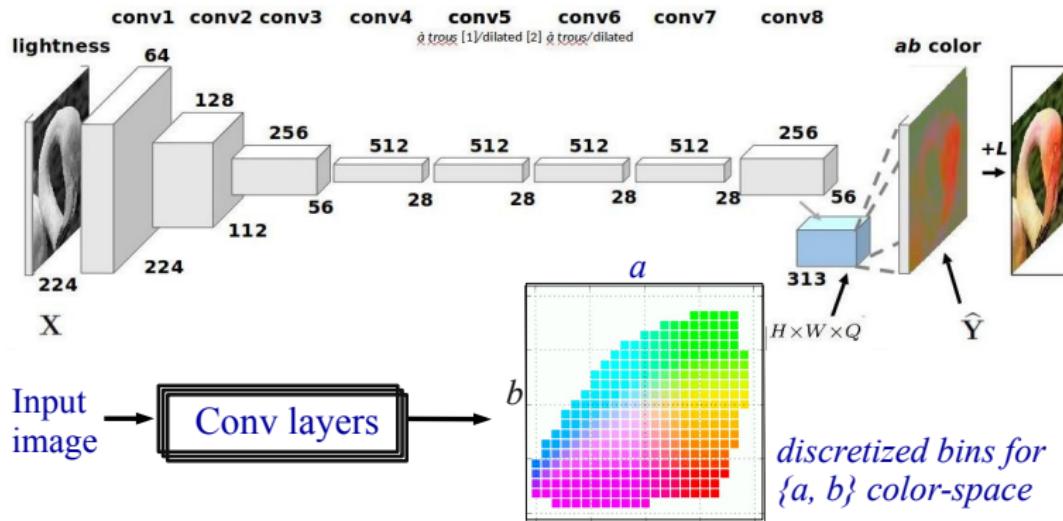
Automatic  
Handles multimodality

### Cons

Depends heavily on reference prior  
Not practical

# Generative Approach

Colorful Image Colorization model [1]



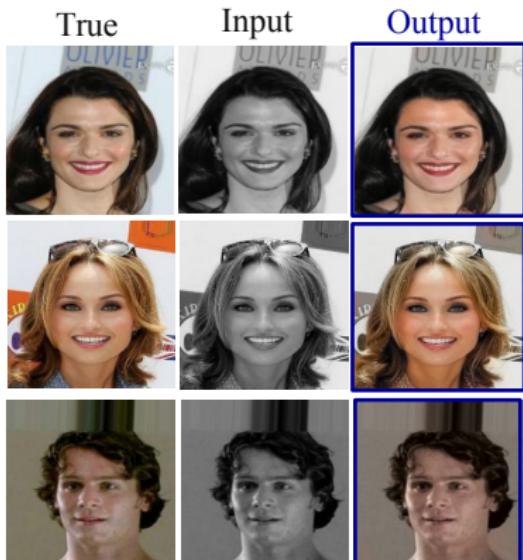
# Colorful Image Colorization model [1]

## Adopted Changes

Model Changes	Original model	Adopted model
Output	Classification Probabilities	Image
Loss function	Cross-entropy based $L_{col}(Z, \hat{Z}) = - \sum_p Z_p \sum_{q \in Q} Z_p[q] \log(\hat{Z}_p[q])$	$L_1 : \lambda \sum_p  I_{AB}[p] - \hat{I}_{AB}[p] $ $L_2 : \lambda \sum_p (I_{AB}[p] - \hat{I}_{AB}[p])^2$
Trained on	ImageNet	CelebA, Places2
Implementation	Caffe	TensorFlow
Training	Not end-to-end	End-to-end

# Results

Colorful Image Colorization model as generator only



CelebA dataset

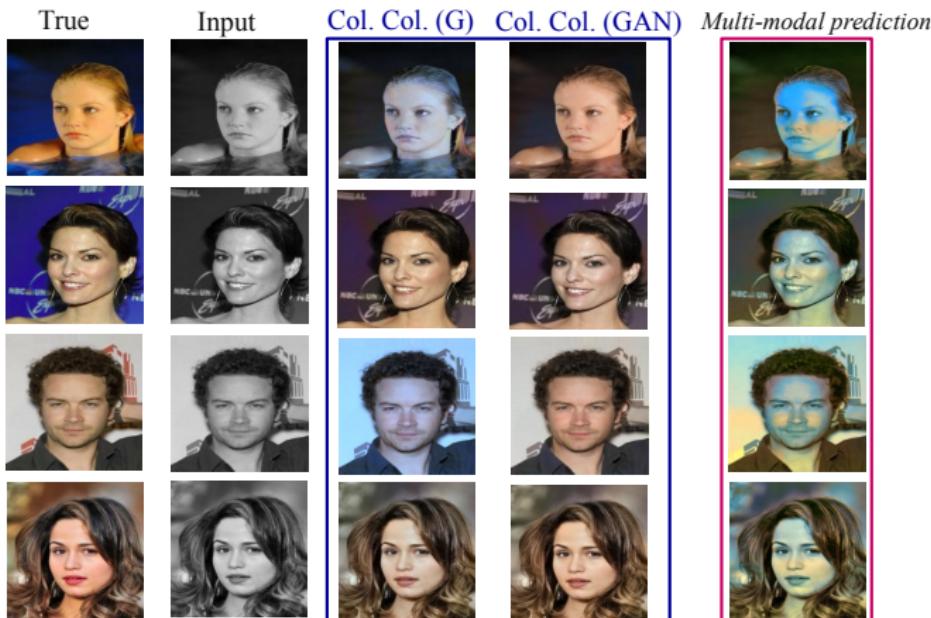


Places2 dataset

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

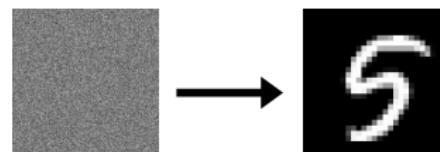
# Results

Colorful Image Colorization model as generator in a GAN



# 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

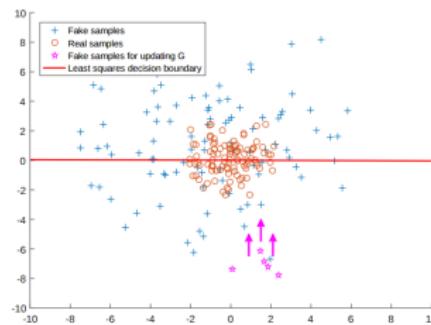


Fig. source: [7]

# GAN Comparison Results

MNIST

GAN, DCGAN

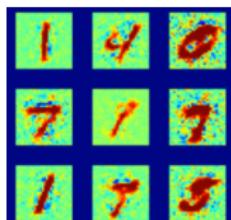
CelebA

EBGAN, WGAN

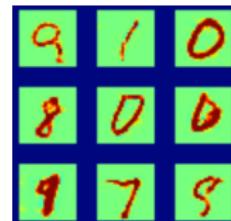
LSUN

LSGAN

GAN



DCGAN



EBGAN



LSGAN

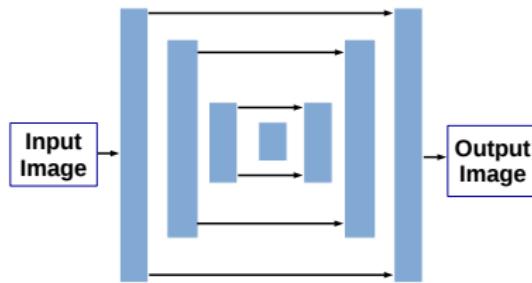


WGAN

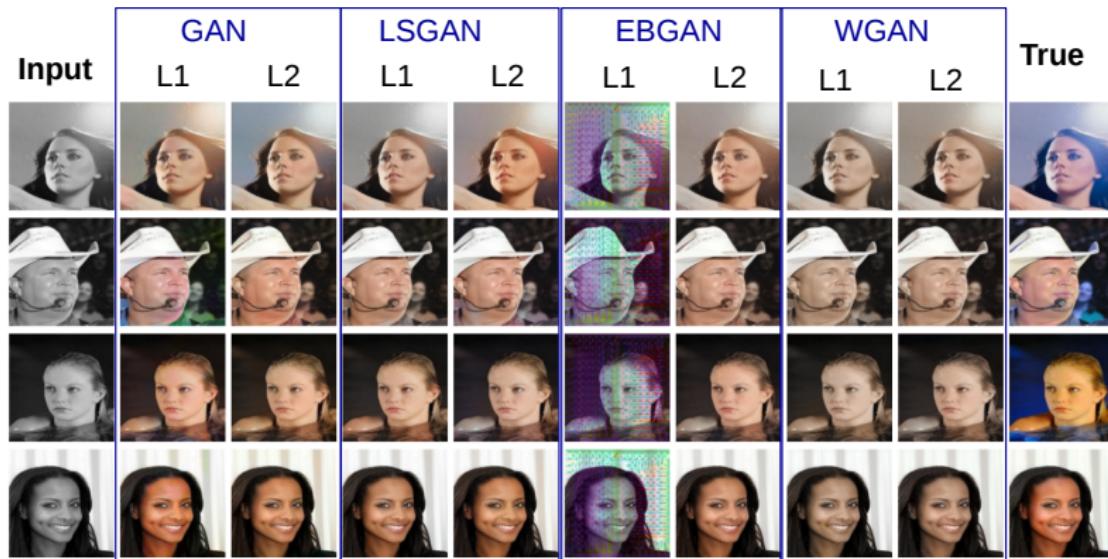


# GANs Towards Colorization

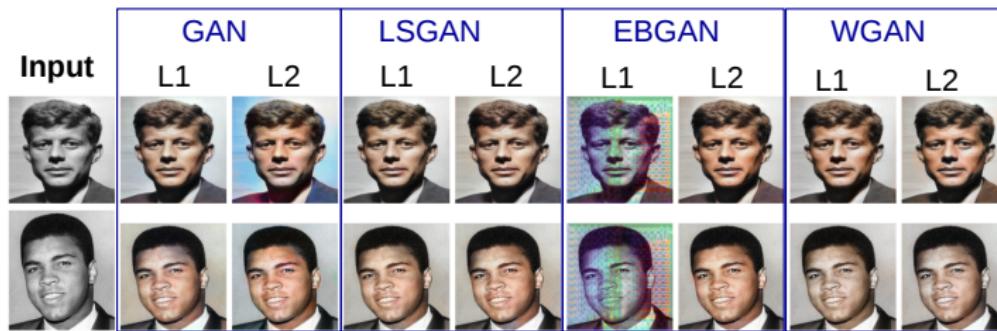
- Tested two generators
  - Pix2Pix
  - Colorful Image Colorization
- Pix2Pix generator is modeled as an encoder-decoder with skip connections
- Combine L1 and L2 loss with GAN Variations



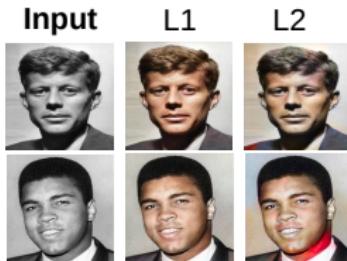
# Results in Comparison



# Legacy Grayscale Results



Pix2Pix model as Generator



Colorful Image Colorization model as Generator

# Conclusions and 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
- Our model
  - 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 Leon Bottou. *Wasserstein gan*. arXiv preprint arXiv:1701.07875 (2017).
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