

Conditional Generative Adversarial Networks

CAMERON FABBRI



Outline

- Generative Adversarial Networks (GANs)
- Wasserstein GANs
- Conditional GANs
- Experiments
- Future Work

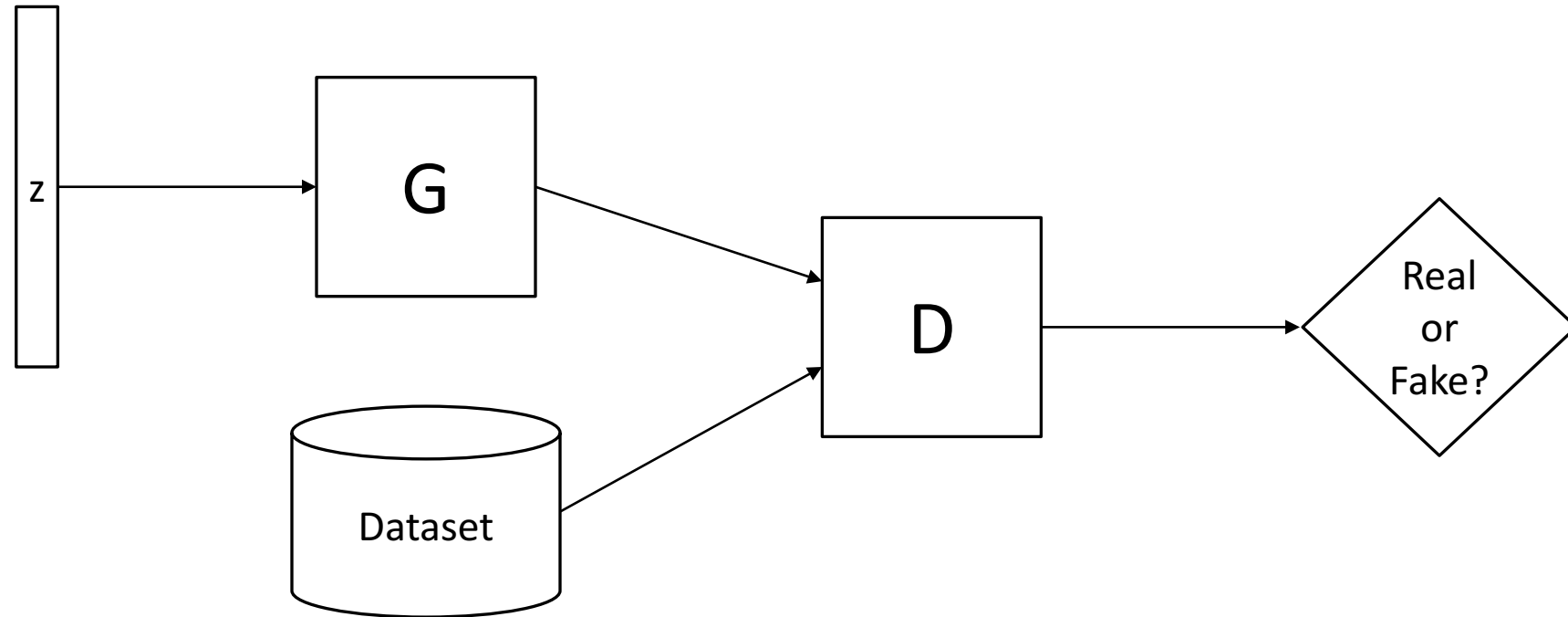
Generative Adversarial Networks (GANs)

- Two player mini-max game
 - Generator **G**
 - Discriminator **D**
- D is trained to discriminate between a real image and a generated image.
- G is trained to fool D

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

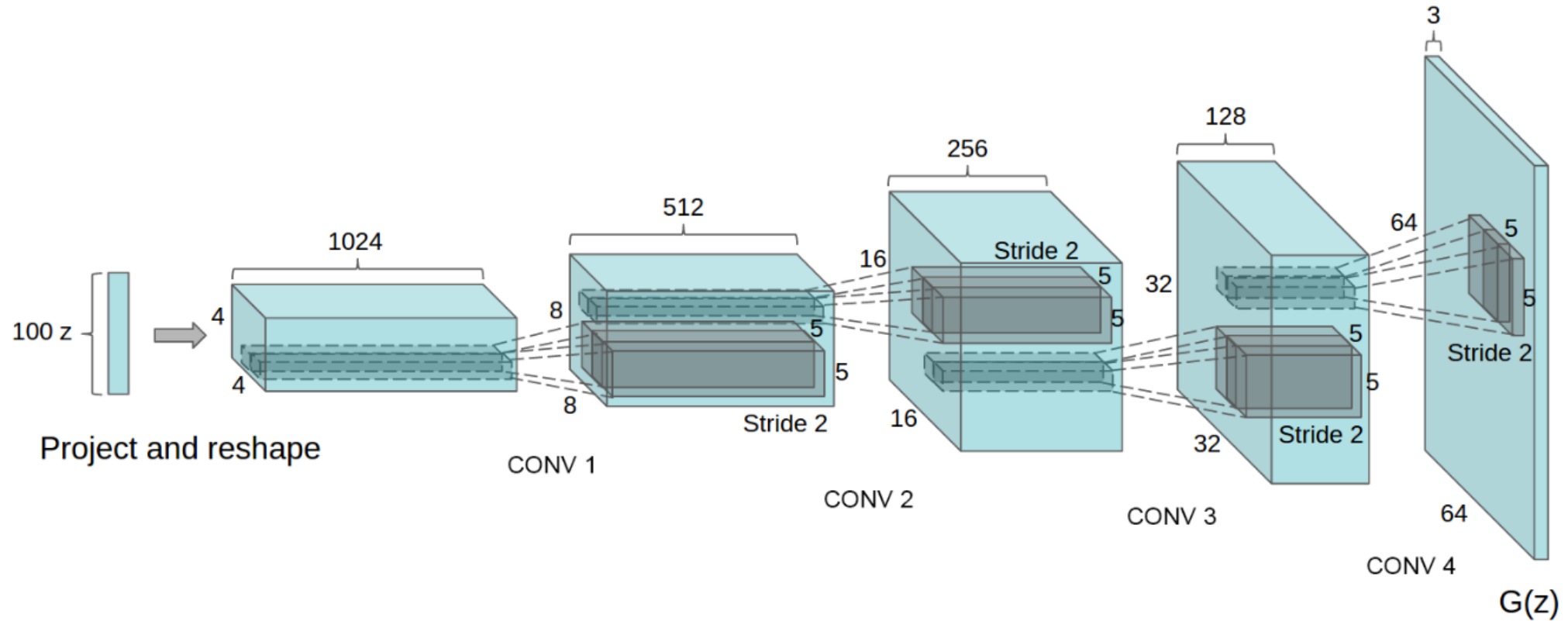
Generative Adversarial Networks

$$z = \mathcal{N}(-1, 1)$$



Deep Convolutional GANs (DCGANs)

- Developed an architecture combining GANs and deep learning



Wasserstein GANs (WGAN)

- The original GAN used D as a classifier, minimizing the Jensen-Shannon Divergence:

$$JS(\mathbb{P}_r, \mathbb{P}_g) = KL(\mathbb{P}_r || \mathbb{P}_m) + KL(\mathbb{P}_g || \mathbb{P}_m)$$

- The Wasserstein GAN applies the Kantorovich-Rubinstein duality to approximate the Wasserstein-1 distance:

$$\min_G \max_{D \in \mathcal{D}} \mathbb{E}_{\mathbf{x} \sim \mathbb{P}_r} [D(\mathbf{x})] - \mathbb{E}_{\tilde{\mathbf{x}} \sim \mathbb{P}_g} [D(\tilde{\mathbf{x}})]$$

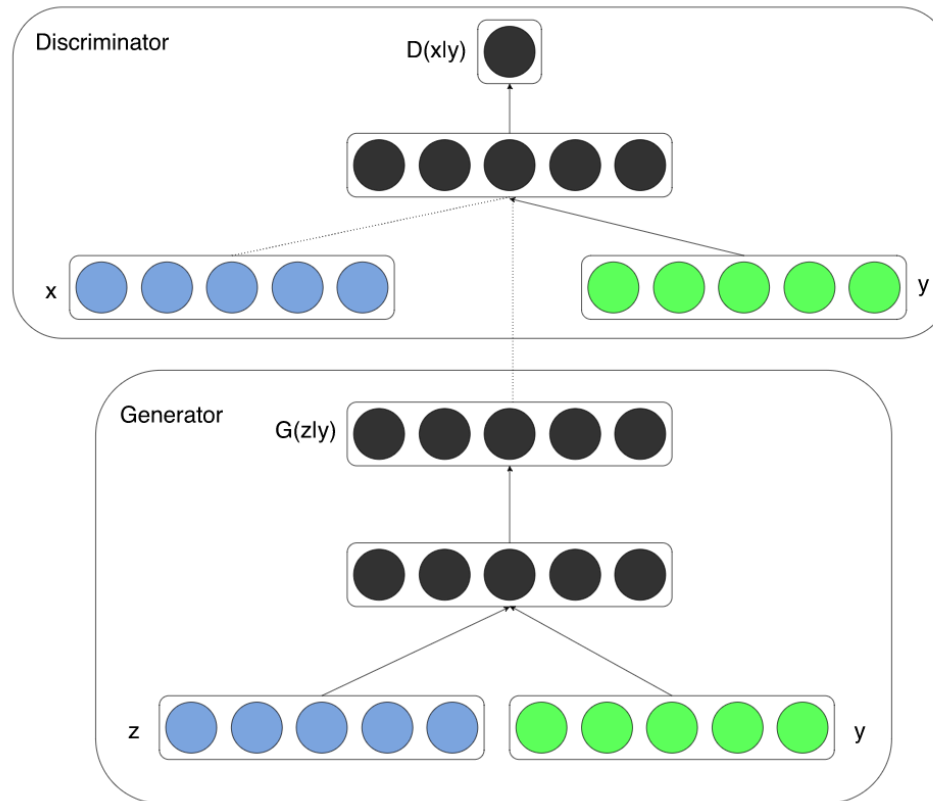
Improved Wasserstein GANs (WGAN-GP)

- A differentiable function is 1-Lipschitz if and only if it has gradients with norm less than or equal to 1 everywhere
 - Idea: Enforce the Lipschitz-1 constraint by penalizing the gradient norm of the discriminator with respect to the input – **not tractable**.
 - Instead penalize the square distance of samples from 1.

$$L = \underbrace{\mathbb{E}_{\tilde{\mathbf{x}} \sim \mathbb{P}_g} [D(\tilde{\mathbf{x}})] - \mathbb{E}_{\mathbf{x} \sim \mathbb{P}_r} [D(\mathbf{x})]}_{\text{Original critic loss}} + \lambda \underbrace{\mathbb{E}_{\hat{\mathbf{x}} \sim \mathbb{P}_{\hat{\mathbf{x}}}} [(\|\nabla_{\hat{\mathbf{x}}} D(\hat{\mathbf{x}})\|_2 - 1)^2]}_{\text{Our gradient penalty}}.$$

Conditional GANs (cGANs)

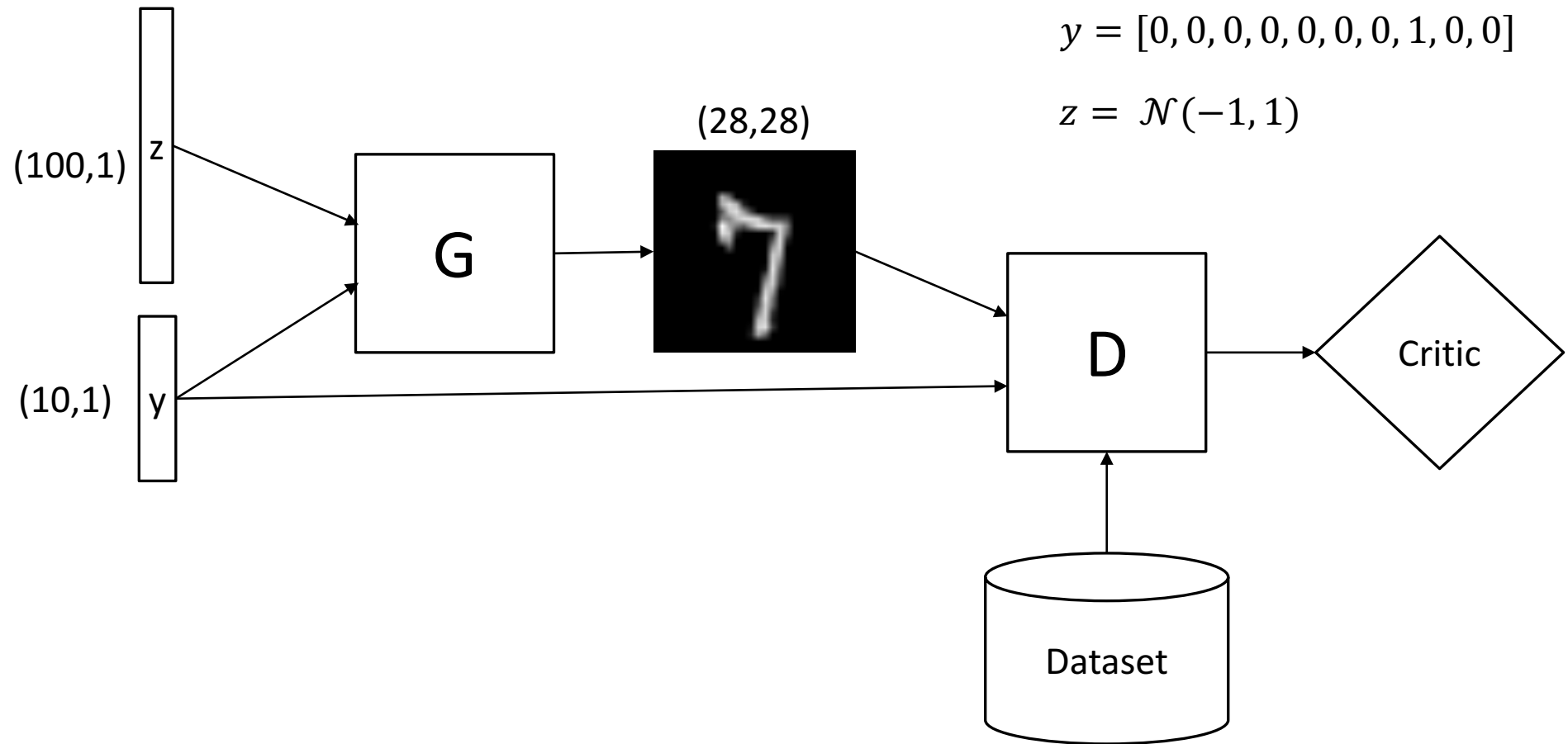
- Introduce some additional information into the generator and discriminator.



Experiments

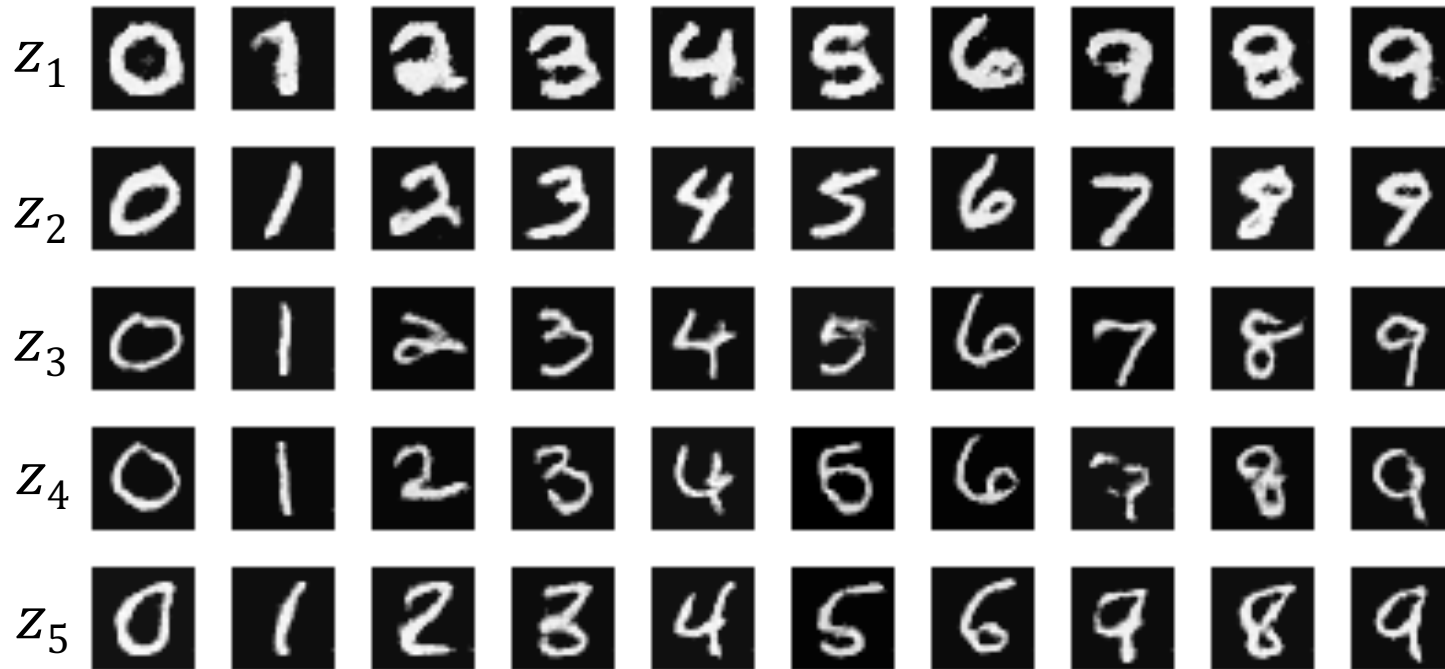
- Implement the Improved Wasserstein method in the conditional GAN setting.
- Control digit generation using MNIST
- Alter visual attributes in faces using the CelebA dataset
- Explore the latent space

MNIST Experiments



Label Alteration

- Each row has the same z vector
- Each column has the same y vector

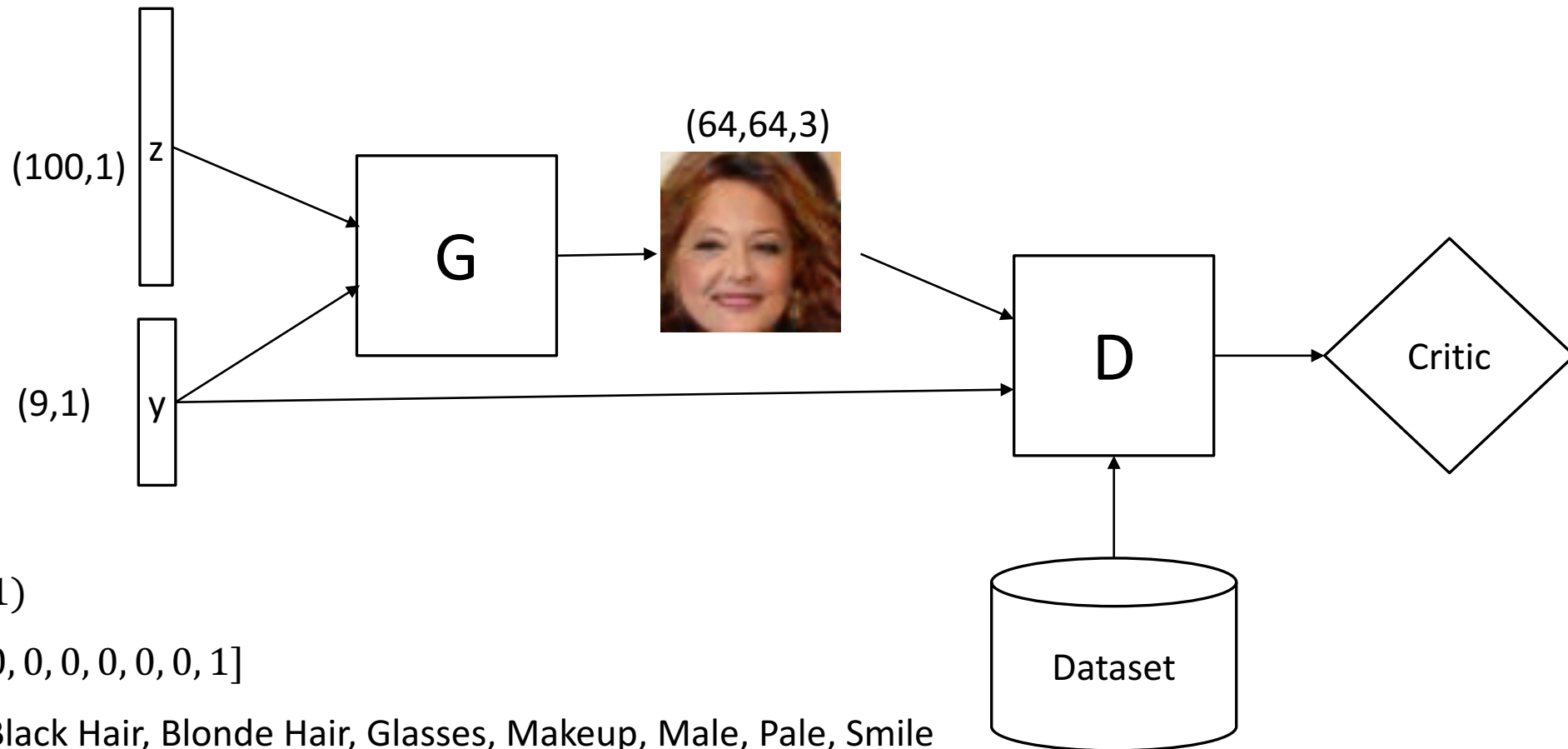


Interpolation

- Interpolate between both z and y vectors



CelebA Experiments

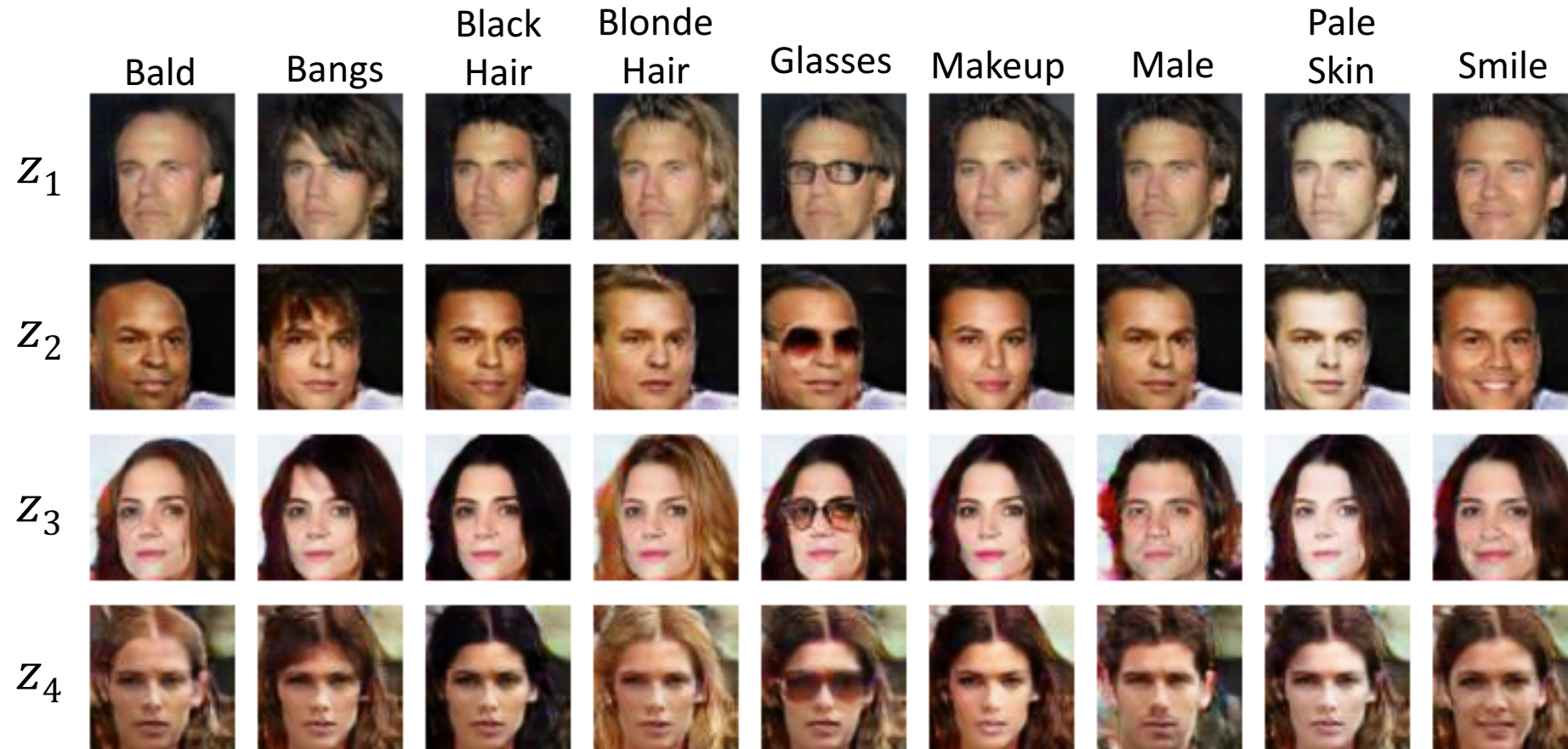


$$z = \mathcal{N}(-1, 1)$$

$$y = [0, 0, 0, 0, 0, 0, 0, 0, 0, 1]$$

Bald, Bangs, Black Hair, Blonde Hair, Glasses, Makeup, Male, Pale, Smile

Attribute Alteration



Interpolation

Bald → Not Bald



Black Hair → Blonde Hair



Female → Male

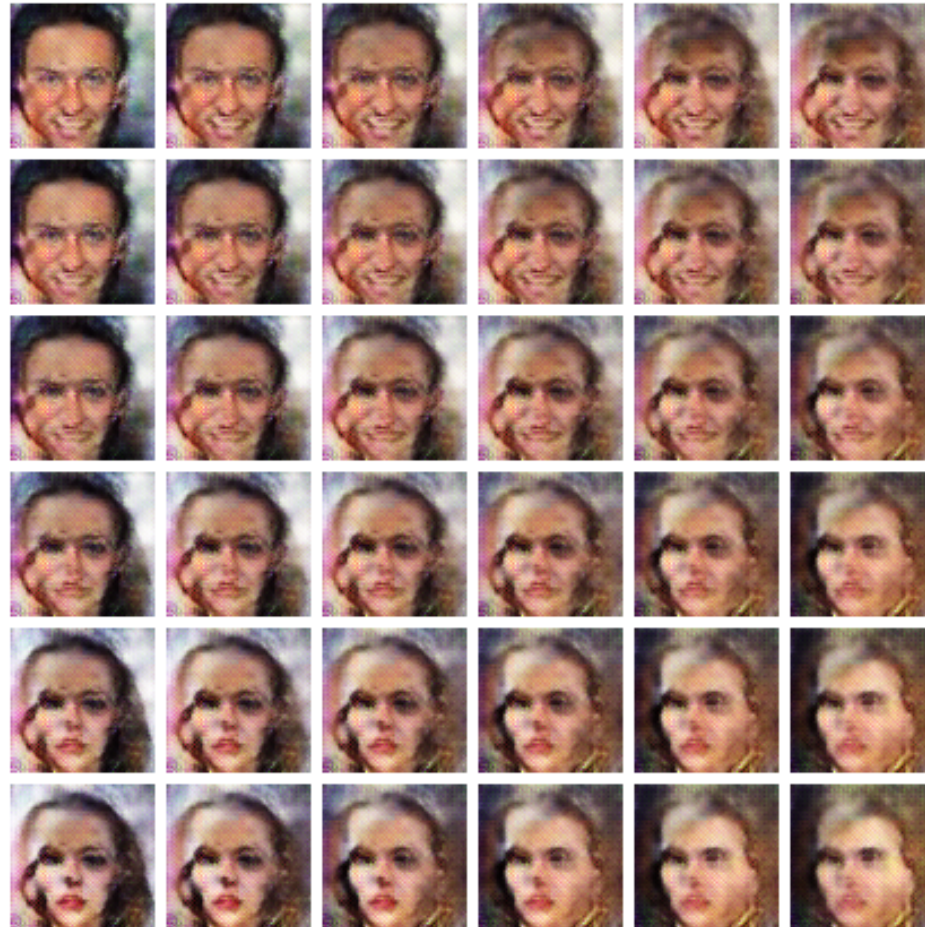


Glasses, Smiling, Bangs →
No Glasses, Not Smiling,
No Bangs, Pale



CelebA Experiments using GAN

Male, Black Hair, Smiling



Female, Smiling

Female, Makeup

Male, Blonde Hair

Conclusion

- Generative Adversarial Networks
 - Wasserstein Method
- Conditional GANs
- Experiments on two datasets
- Future Work
 - Try on other datasets
 - Compare with other GAN methods
 - Least Squares GANs
 - Energy Based GANs

References

- [1] Goodfellow, Ian, et al. "Generative adversarial nets." *Advances in neural information processing systems*. 2014.
- [2] Mirza, Mehdi, and Simon Osindero. "Conditional generative adversarial nets." *arXiv preprint arXiv:1411.1784* (2014).
- [3] Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "Wasserstein gan." *arXiv preprint arXiv:1701.07875* (2017).
- [4] Gulrajani, Ishaan, et al. "Improved training of wasserstein gans." *arXiv preprint arXiv:1704.00028* (2017).
- [5] Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* (2015).

Thank you

Questions?

Code: <https://github.com/cameronfabbri/cWGANs>