Team #3

MVM+ : Generative Model via Adversarial Metric Learning

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Introduction

GAN vs MVM

Differences	GANs	MvM
Main point of view	statistics	geometry
Matching terms	means, moments, etc.	centroids, p-diameters
Matching criteria	statistical discrepancy	learned distances
Underlying metric	default Euclidean	learned intrinsic
Objective functions	one min-max value function	two distinct objectives

- GAN
  - Statistical approach
- MVM
  - ICCV 2021 (Microsoft)
  - Geometrical approach

Related Works

Curse of Dimensionality

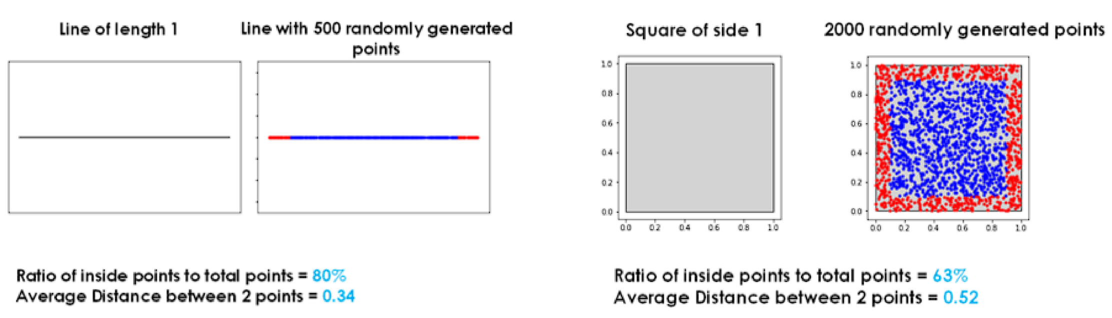


Figure 1. The probability of generating a random sample in a space within the edge of the space (within 10%) and the average distance between the two samples. Left: 1D, Right: 2D

- The larger the dimension, the sparse the data.
- Distance metrics (Euclidean, Manhattan, etc) lose meaning

Deep Metric Learning

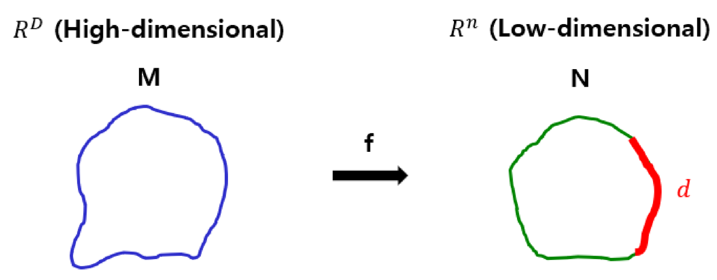
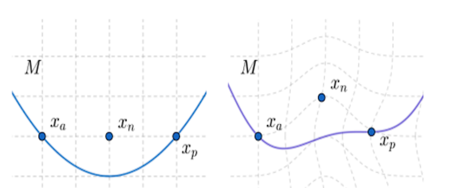


Figure 2. Procedure of deep metric learning

- Embedding
  - $f : M \to N$
  - Euclidean loss create manifold (N, h)
  - Learning the metric (M, g) through pullback of (N, h)
- **Metric learning**
  - Process of specifying **relationships & metrics** between samples
  - In the dimensionally reduced space R^n.

Baseline Methodology

Triplet Loss



No performance diff.

$$L_{apn} = \max\{0, \cancel{d^2(x_a, x_p) - d^2(x_a, x_n)} + \alpha - \gamma Cos(g_w(x_n) - g_w(x_a), g_w(x_p) - g_w(x_a))\}$$

Figure 3. Left: Visualization of the manifold optimized by the triplet loss. Right: Triplet loss

- Assume the triplet loss will flatten the round part of the manifold
  - Geodesic distance = Euclidean distance
- Problem
  - The assumption that the triplet loss flattens the manifold is incorrect → MVM weakness 1
  - In fact, in the learning process, the cosine similarity factor, not the distance part of the triplet loss, is important.

Manifold Matching Loss

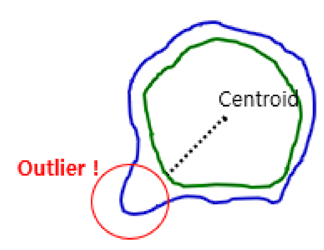


Figure 4. A drawback of the manifold matching loss, which is its inability to account for outliers.

- Estimate the shape of the manifold M through sample points
  - Center of M → Frechet mean
  - Size of M → p-diameter
- Problem
  - Assume that the shape of M hyper-sphere like → MVM weakness 2
  - Does not reflect the outliers of M at all
  - What if M has a unique shape?

Improved Methodology

Cosine Similarity Loss

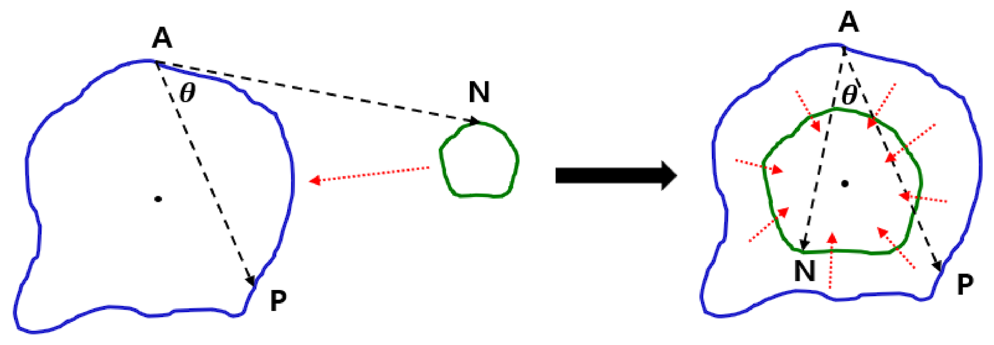


Figure 5. The effect when optimized with the cosine similarity loss.

$$L_{apn} = -Cos(g_w(x_n) - g_w(x_a), g_w(x_p) - g_w(x_a))$$

- Designate anchor and positive in the real data manifold, one sample of negative in generated data manifold
- Narrows the angle between the specified three samples
- Effect
  - Preserve real **data manifold geometry**
  - Include generated data manifold in center of Real data manifold without violating the shape

Average Hausdorff Distance Loss

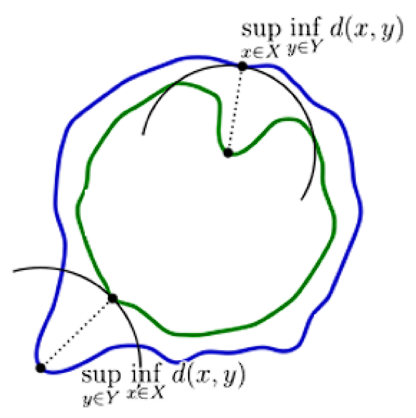


Figure 6. The effect when optimized with the average Hausdorff distance loss.

$$\widetilde{\delta_h}(A,B) = \max_{a \in A} \min_{b \in B} \| a - b \|$$

$$d_{AH}(X,Y) = \frac{1}{|X|} \sum_{x \in X} \min_{y \in Y} d(x,y) + \frac{1}{|Y|} \sum_{y \in Y} \min_{x \in X} d(x,y)$$

- Use hausdorff distance for manifold matching
- Create a production data manifold Y condensed on the real data manifold X

MVM+ Pipeline

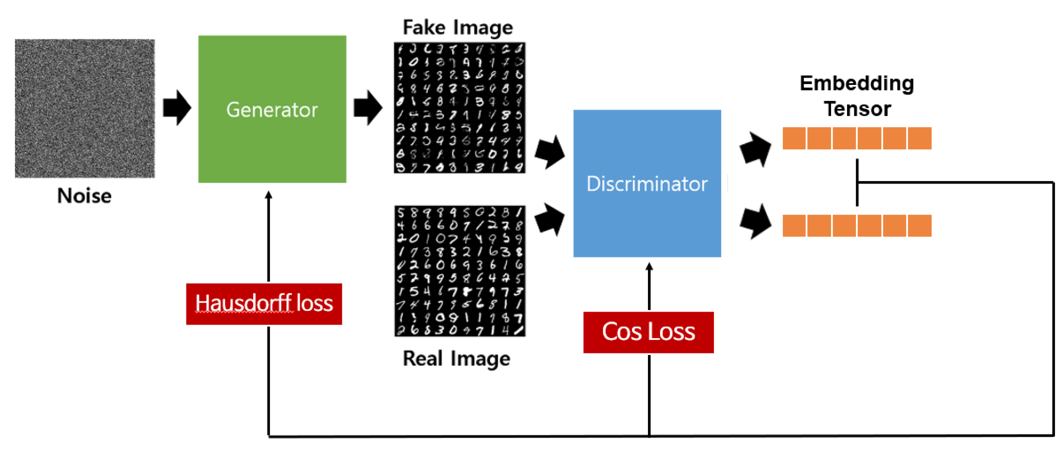


Figure 7. Pipeline of MVM+ framework

Experiment

Synthetic Data Generation

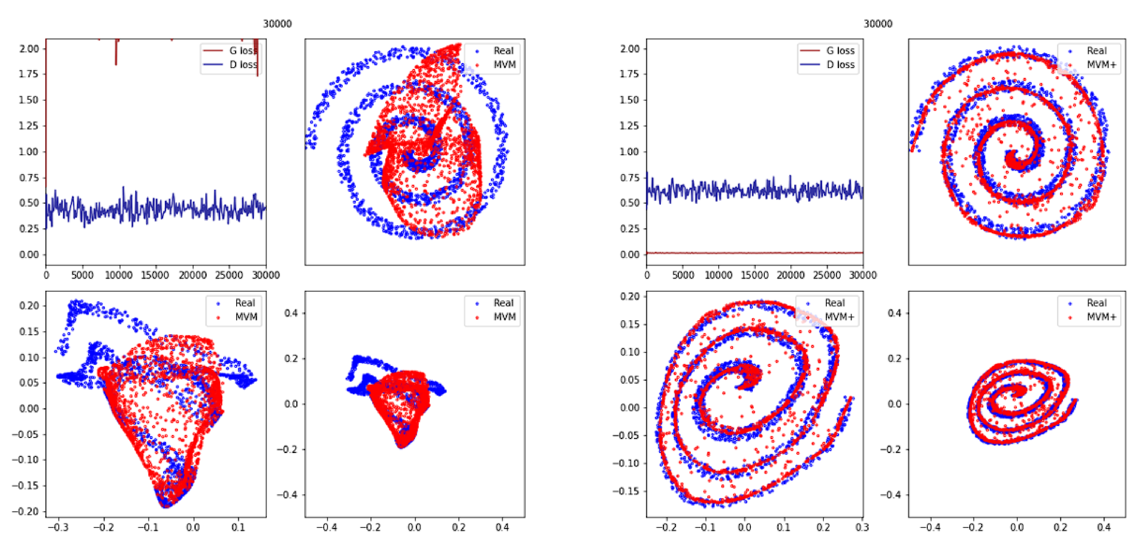


Figure 8. Results of synthetic data generation and tendency of loss for spiral data. **Left**: MVM, **Right**: MVM+

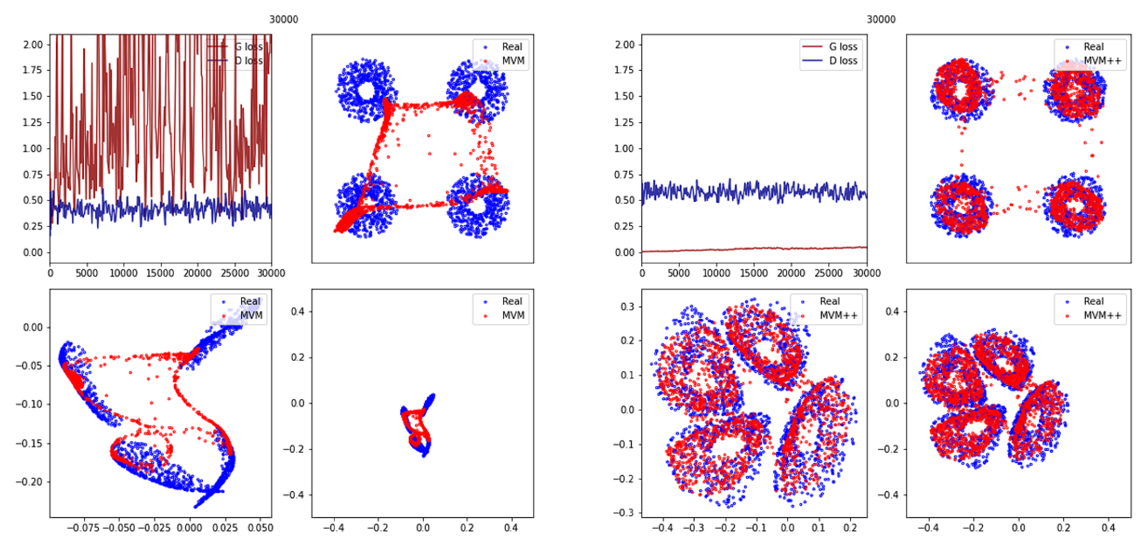


Figure 9. Results of synthetic data generation and the tendency of loss for manifold data. **Left**: MVM, **Right**: MVM+

Image Generation

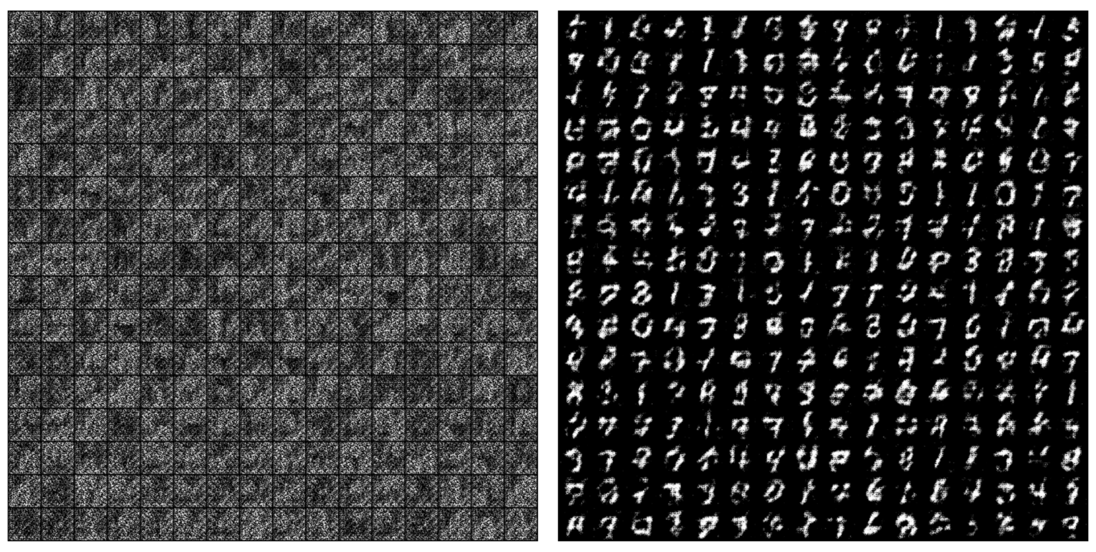


Figure 10. The result of data generation for MNIST dataset (epoch 1) **Left**: MVM, **Right**: MVM+

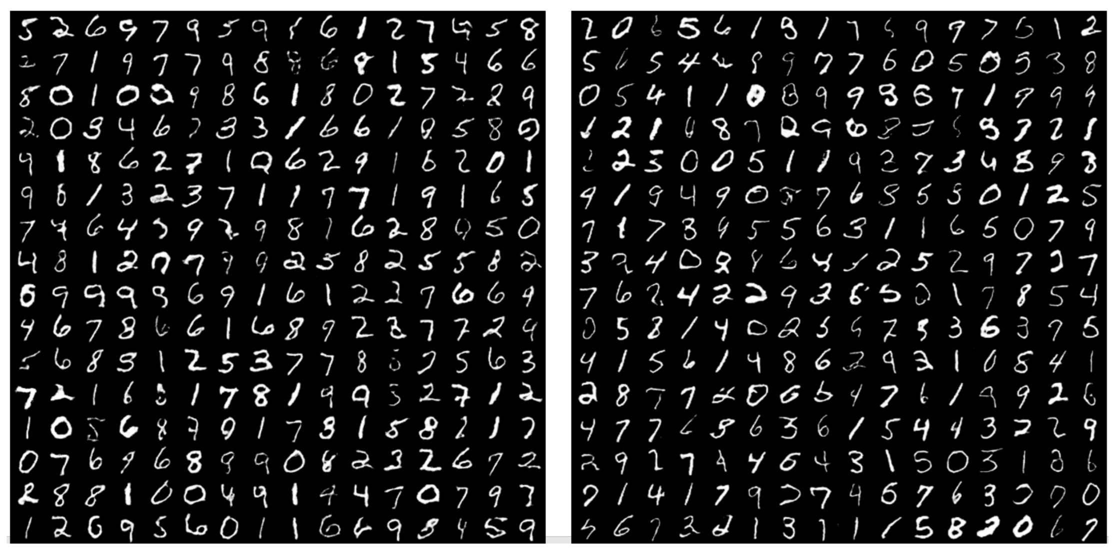


Figure 11. The result of data generation for MNIST dataset (epoch 100) **Left**: MVM, **Right**: MVM+

Figure 12. The result of data generation for celebA dataset Left: MVM, Right: MVM+

Figure 13. High resolution image generation

Visualize and Targeting with MVM+

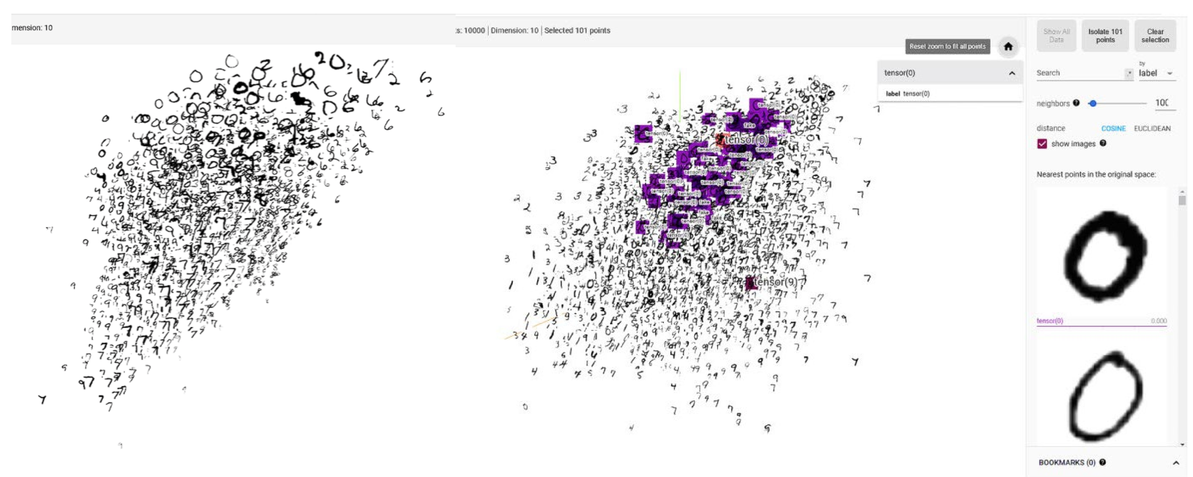


Figure 14. Generated data visualization and search of MVM+ for MNIST dataset.

Conclusion

- Represent and generate data from a geometric rather than statistical point of view.
- Improved stability and generation ability by supplementing the shortcomings of the existing MVM
- As a result of learning, MVM+ can:
  - Visualize what the sample dataset looks like in data space
  - Represent similarity between data (near data and far data)
  - You can target and generate generated data close to specific sample data.

References

[1] Mengyu Dai and Haibin Hang, Manifold Matching via Deep Metric Learning for Generative Modeling, ICCV 2021