Manifold Learning of Face Data

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Introduction

Objective

- Our work explores manifold learning on human face image data.
- In particular, we investigate whether distance metrics in lower dimensional space capture visual similarity better than euclidean distance between original images.

Dataset Used

We use the CelebA Dataset with more than 200K celebrity images covering large pose variations and background clutter.

For computational tractability, we randomly sample ~ 6500 images from the CelebA dataset for our purposes.

Example Images

Figure 1: Some random images from the Dataset

Our Approach

A Bird's eye view

- Step 1: Project onto a Lower Manifold
  - IsoMap Projection
- Step 2: Sample new points on the Learned Manifold
  - Convex combination between selected Images
- Step 3: Reconstruction of new images from sampled points
  - Extremal Randomized Tree Regressor
  - Convex combination in the higher dimensional space

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- Following this, we follow the remaining MDS algorithm.

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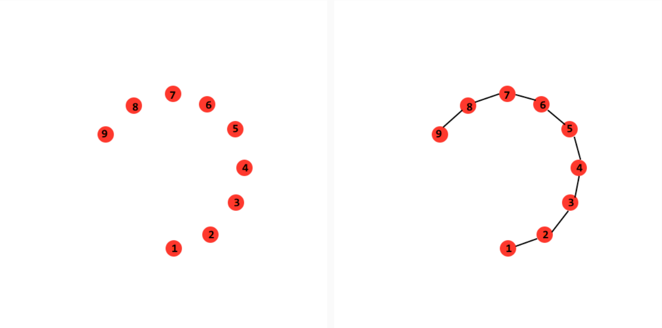

(a) Sample Data (b) Graph

Figure 2: Data with and without graph

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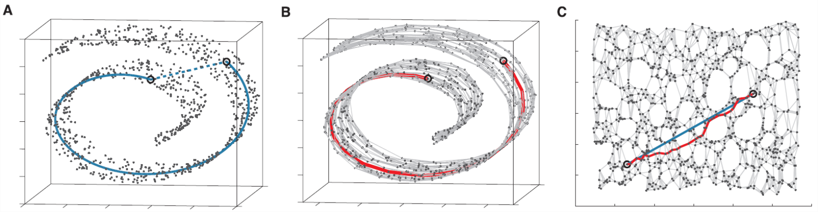
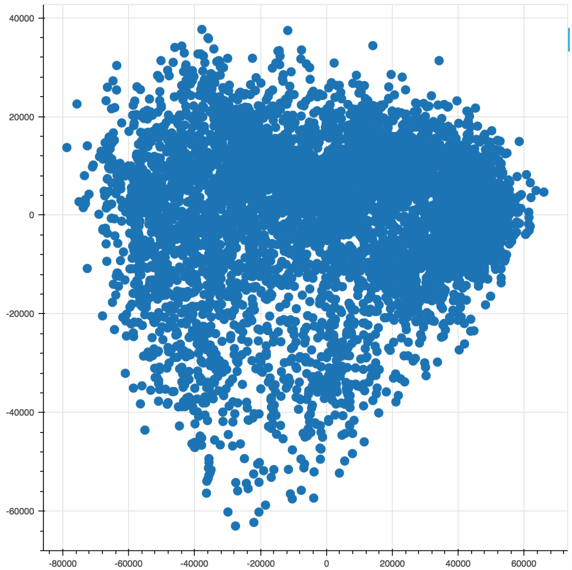


Path Selection and Sampling



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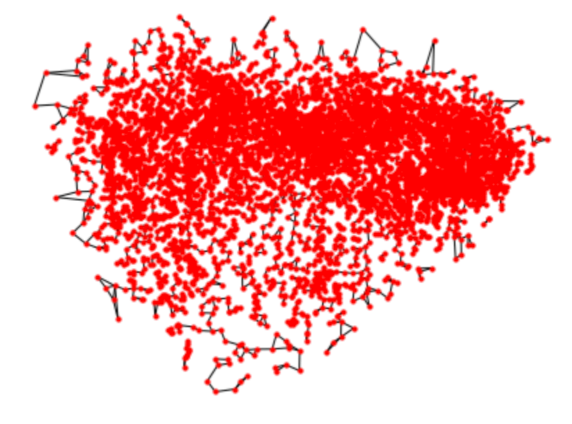
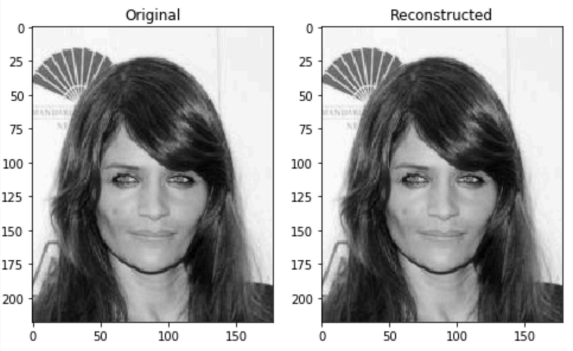


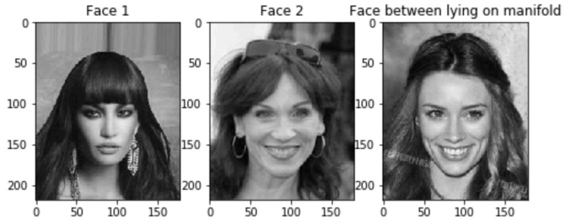
- Convex Combination between neighbors

Reconstruction : Projecting back to the image domain

- Need representation for these sub-sampled points in the original image space
- Method to map sub-samples back to the higher dimension
- Multilayer Perceptron, Random Forest, Kernerlized Linear Regressor, Extremely Randomized Tree Regressor

Reconstruction





Recontruction : A closer look at the Regressor

- Method 1 Sample Video

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- Method 1 Sample Video
- Jump Discontinuities
- What's wrong? Embedding or Reconstruction?
- Look for linearity in image norms!

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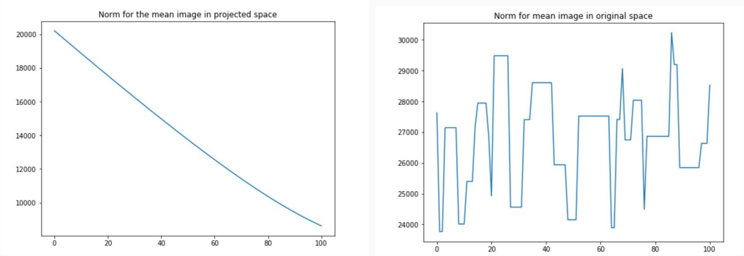
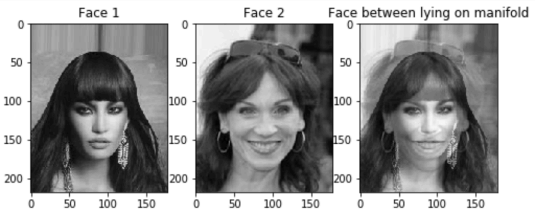


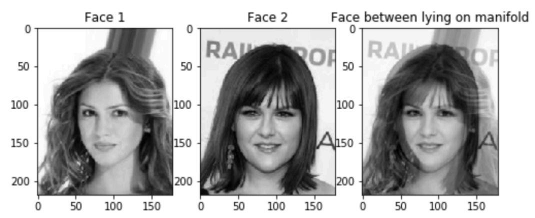
(a) IsoMap Embedded Manifold **(b)** Original Image domain

Figure 3: Total Variation norm for sampled images

Reconstruction : Working Around

- Given the path, we can sub-sample in the higher dimension
- Take convex combination of images in higher-dim to generate new ones





A cool Souvenir : Morphing Video

- Exhibit A
- Exhibit B
- Exhibit C

Questions?