

PCA, RPCA, and ISOMAP

Outline

- ▶ PCA vs. Robust PCA
- ▶ Multi-Dimensional Scaling (MDS)

PCA vs. Robust PCA

Goal.

- ▶ Reduce the dimensions of the feature matrix $X \in \mathbb{R}^{n \times d}$
- ▶ Compute $Z \in \mathbb{R}^{n \times k}$ where $k \ll d$
- ▶ k is user-defined

Objective function

$$\begin{aligned} f(W, Z) &= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^d (w_j^T z_i - x_{ij})^2 \\ &= \frac{1}{2} \|ZW - X\|_F^2 \end{aligned} \tag{1}$$

PCA vs. Robust PCA

$$f(W, Z) = \frac{1}{2} \|ZW - X\|_F^2 \quad (Z \in \mathbb{R}^{n \times k}, W \in \mathbb{R}^{k \times d}) \quad (2)$$

Algorithm.

1. Optimize w.r.t Z while keeping W fixed

$$Z^* = \arg \min_Z \frac{1}{2} \|ZW - X\|_F^2$$

2. Optimize w.r.t W while keeping Z fixed

$$W^* = \arg \min_W \frac{1}{2} \|ZW - X\|_F^2$$

3. Repeat steps 1 and 2 until convergence

PCA vs. Robust PCA

At train time: * Get Z * Train a logistic regression

- ▶ Motivation: PCA is used for dimensionality reduction (to speed up training and testing time)

PCA

$$\arg \min_{Z,W} \frac{1}{2} \|ZW - X\|_F^2 \quad (Z \in \mathbb{R}^{n \times k}, W \in \mathbb{R}^{k \times d}) \quad (3)$$

Given code. For optimizing w.r.t Z and W , respectively.

```
def _fun_obj_z(self, z, w, X, k):  
    n,d = X.shape  
    Z = z.reshape(n,k)  
    W = w.reshape(k,d)  
    R = np.dot(Z,W) - X  
    f = np.sum(R**2)/2  
    g = np.dot(R, W.transpose())  
    return f, g.flatten()
```

```
def _fun_obj_w(self, w, z, X, k):  
    n,d = X.shape  
    Z = z.reshape(n,k)  
    W = w.reshape(k,d)  
    R = np.dot(Z,W) - X  
    f = np.sum(R**2)/2  
    g = np.dot(Z.transpose(), R)  
    return f, g.flatten()
```

Robust PCA

$$\arg \min_{Z, W} \|ZW - X\|_1 \quad (Z \in \mathbb{R}^{n \times k}, W \in \mathbb{R}^{k \times d}) \quad (4)$$

Use the smooth approximation of the L1 norm

$$\alpha \approx \sqrt{\alpha^2 + \epsilon}$$

Write the code for optimizing w.r.t Z and W , respectively.

```
def _fun_obj_z(self, z, w, X, k):  
    f = ?  
    g = ?  
    return f, g.flatten()  
  
def _fun_obj_w(self, w, z, X, k):  
    f = ?  
    g = ?  
    return f, g.flatten()
```

Multi-Dimensional Scaling

Goal To represent the data points in lower dimensional space $k \ll d$ such that the similarities between them is retained.

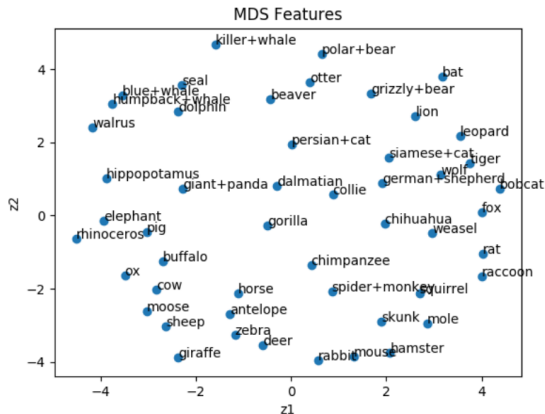
$$f(Z) = \frac{1}{2} \sum_{i=1}^n \sum_{j=i+1}^n (\|z_i - z_j\| - \|x_i - x_j\|)^2 \quad (z_i \in \mathbb{R}^k, x_i \in \mathbb{R}^d) \quad (5)$$

- ▶ Optimize for the new data points directly
 - ▶ Is MDS parametric or not ?

Multi-Dimensional Scaling

$$f(Z) = \frac{1}{2} \sum_{i=1}^n \sum_{j=i+1}^n (||z_i - z_j|| - ||x_i - x_j||)^2 \quad (z_i \in \mathbb{R}^2, x_i \in \mathbb{R}^d)$$

(6)



Multi-Dimensional Scaling (Code)

$$\arg \min_Z \frac{1}{2} \sum_{i=1}^n \sum_{j=i+1}^n (\|z_i - z_j\| - \|x_i - x_j\|)^2 \quad (z_i \in \mathbb{R}^k, x_i \in \mathbb{R}^d)$$

```
def compress(self, X):  
    n = X.shape[0]  
    k = self.k  
  
    # Compute Euclidean distances (Unique to MDS)  
    D = utils.euclidean_dist_squared(X,X)  
    D = np.sqrt(D)  
  
    # Initialize low-dimensional representation with PCA  
    Z = PCA(k).fit(X).compress(X)  
  
    # Solve for the minimizer  
    z = find_min(self._fun_obj_z, Z.flatten(), 500, False, D)  
    Z = z.reshape(n, k)  
    return Z
```

Assignment: Implement ISOMAP

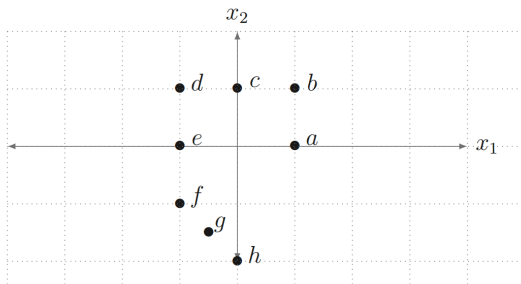
Same objective function as MDS:

$$\arg \min_Z \frac{1}{2} \sum_{i=1}^n \sum_{j=i+1}^n (\|z_i - z_j\| - \|x_i - x_j\|)^2 \quad (z_i \in \mathbb{R}^k, x_i \in \mathbb{R}^d)$$

```
def compress(self, X):  
    n = X.shape[0]  
    k = self.k  
  
    # Compute Euclidean distances (Unique to MDS)  
  
    YOUR CODE HERE. DISTANCES ARE COMPUTED USING GEODISTIC DISTANCE  
  
    # Initialize low-dimensional representation with PCA  
    Z = PCA(k).fit(X).compress(X)  
  
    # Solve for the minimizer  
    z = find_min(self._fun_obj_z, Z.flatten(), 500, False, D)  
    Z = z.reshape(n, k)  
    return Z
```

ISOMAP: Compute Geodistic distance

- Create a distance matrix using geodesic distances, where k



$= 2$

ISOMAP: Answer

| | <i>a</i> | <i>b</i> | <i>c</i> | <i>d</i> | <i>e</i> | <i>f</i> | <i>g</i> | <i>h</i> |
|----------|----------|----------|------------|----------------|----------------|----------------|-------------------|-----------------|
| <i>a</i> | 0 | 1 | $\sqrt{2}$ | $\sqrt{2} + 1$ | $\sqrt{2} + 2$ | $\sqrt{2} + 3$ | $1.5\sqrt{2} + 3$ | $2\sqrt{2} + 3$ |
| <i>b</i> | | 0 | 1 | 2 | 3 | 4 | $0.5\sqrt{2} + 4$ | $\sqrt{2} + 4$ |
| <i>c</i> | | | 0 | 1 | 2 | 3 | $0.5\sqrt{2} + 3$ | $\sqrt{2} + 3$ |
| <i>d</i> | | | | 0 | 1 | 2 | $0.5\sqrt{2} + 2$ | $\sqrt{2} + 2$ |
| <i>e</i> | | | | | 0 | 1 | $0.5\sqrt{2} + 1$ | $\sqrt{2} + 1$ |
| <i>f</i> | | | | | | 0 | $0.5\sqrt{2}$ | $\sqrt{2}$ |
| <i>g</i> | | | | | | | 0 | $0.5\sqrt{2}$ |
| <i>h</i> | | | | | | | | 0 |