

Assignment 1

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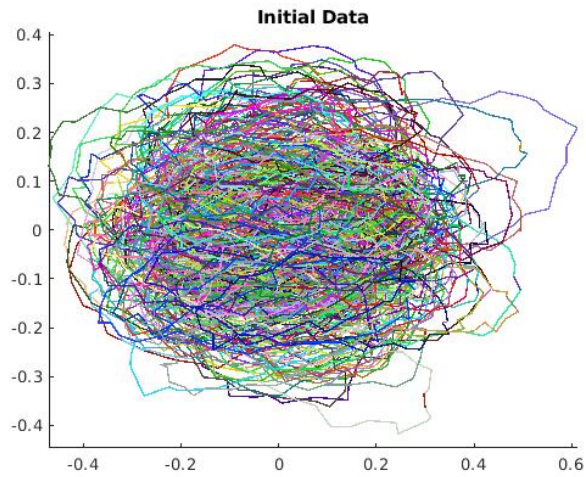
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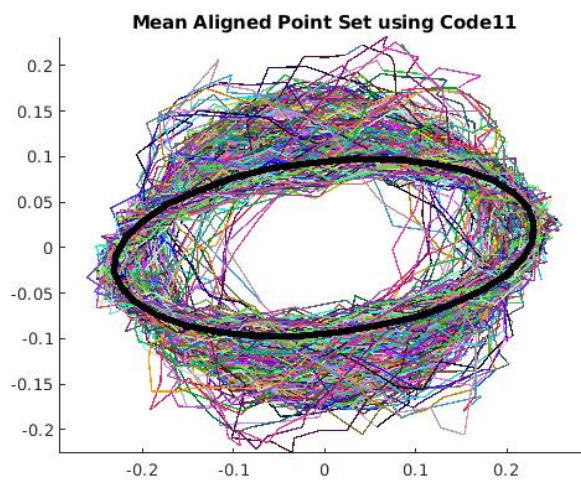
Question 1

Initial Data

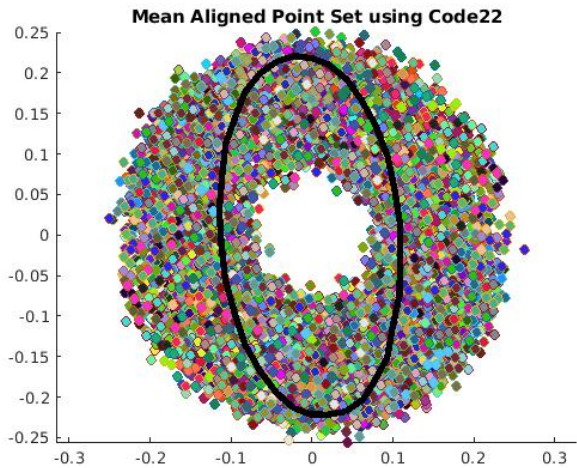


Mean Aligned Data

Using Code 11

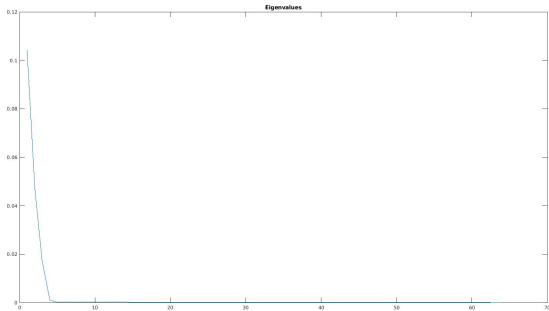


Using Code 22

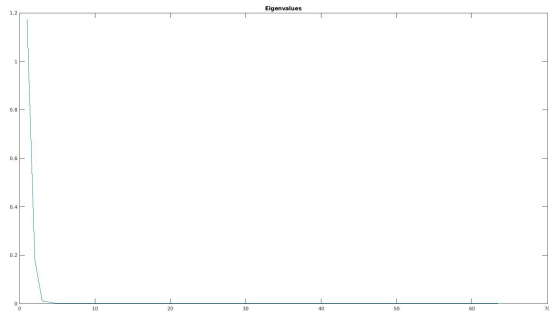


Eigenvalue Plots

Using Code 11

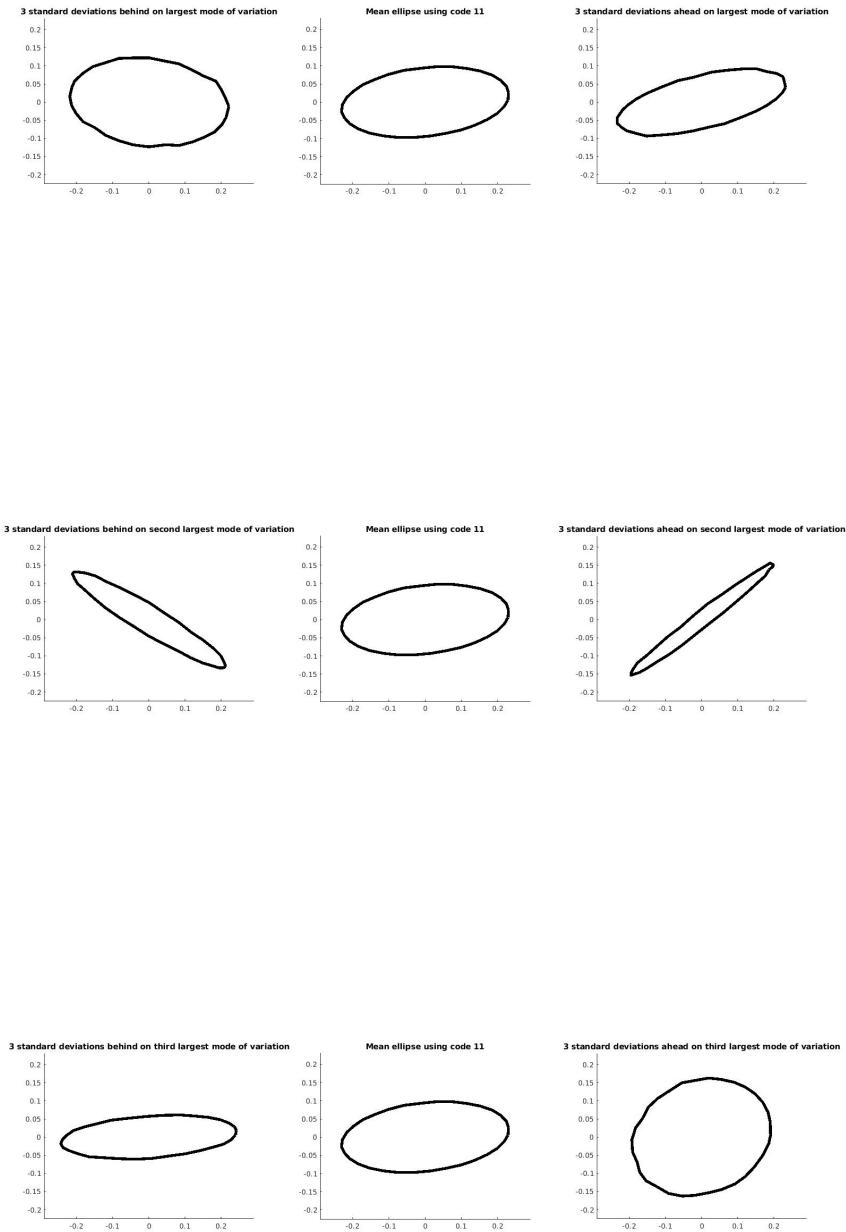


Using Code 22

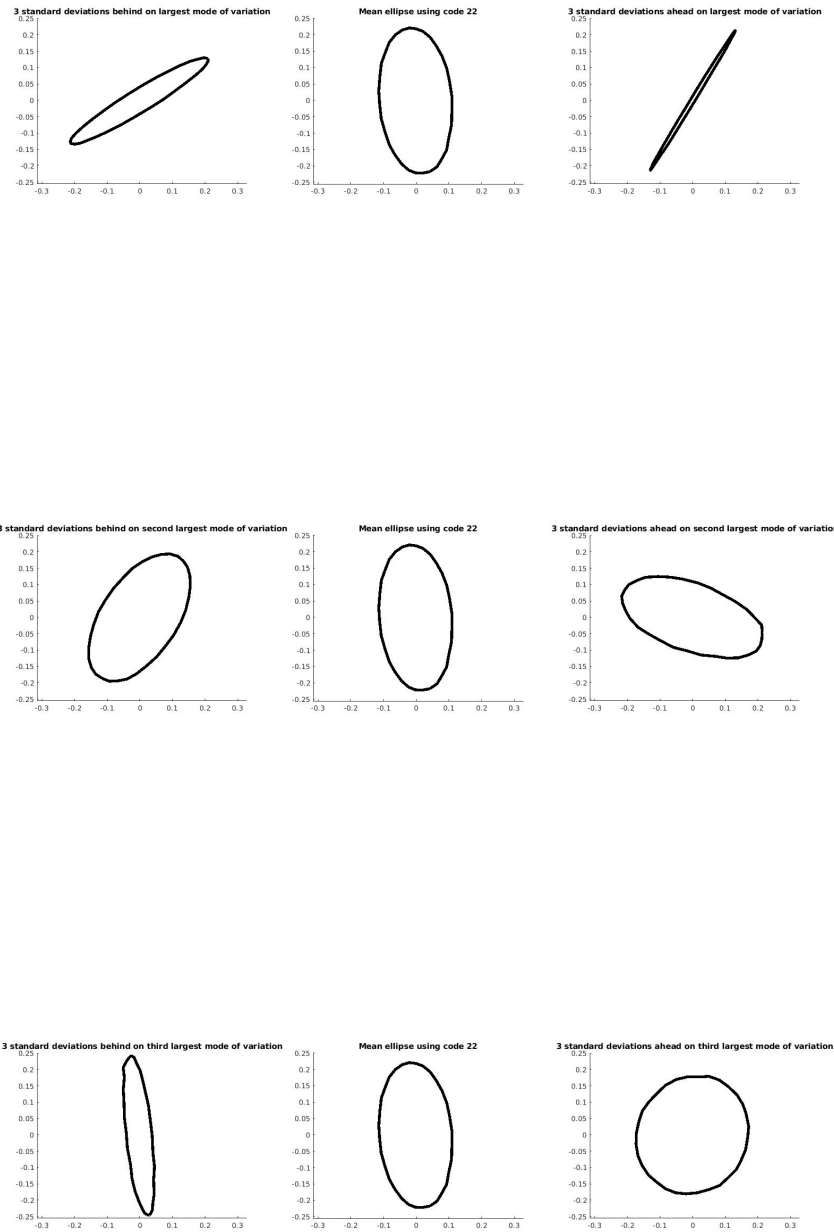


Variance along top 3 directions

Using Code 11

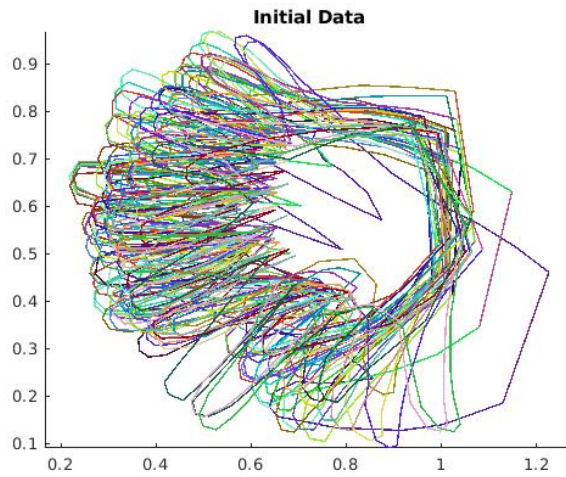


Using Code 22



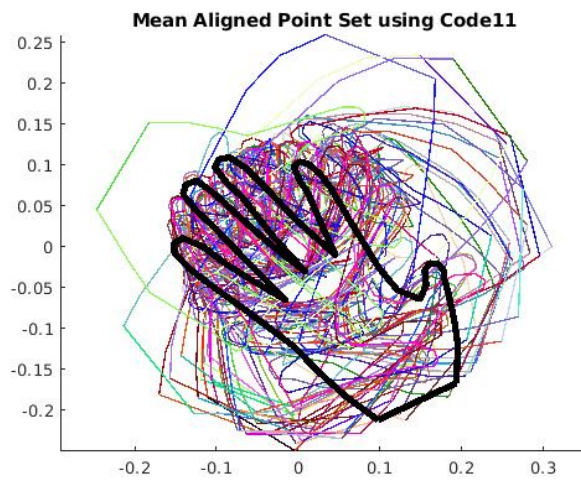
Question 2

Initial Data

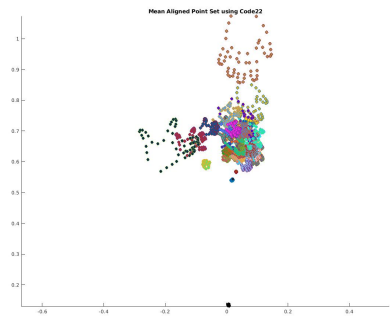


Mean Aligned Data

Using Code 11

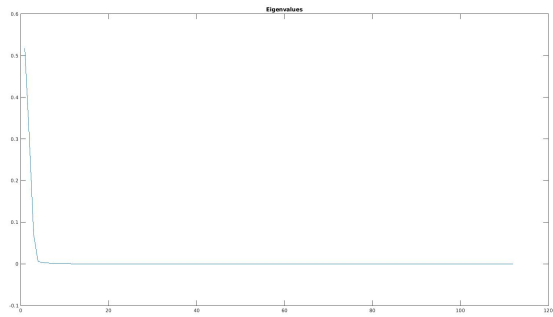


Using Code 22

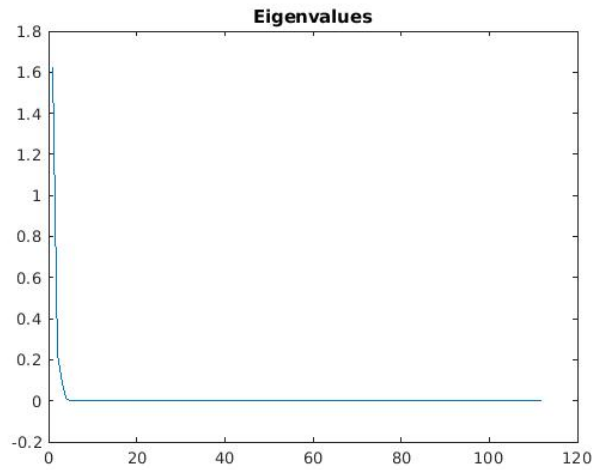


Eigenvalue Plots

Using Code 11

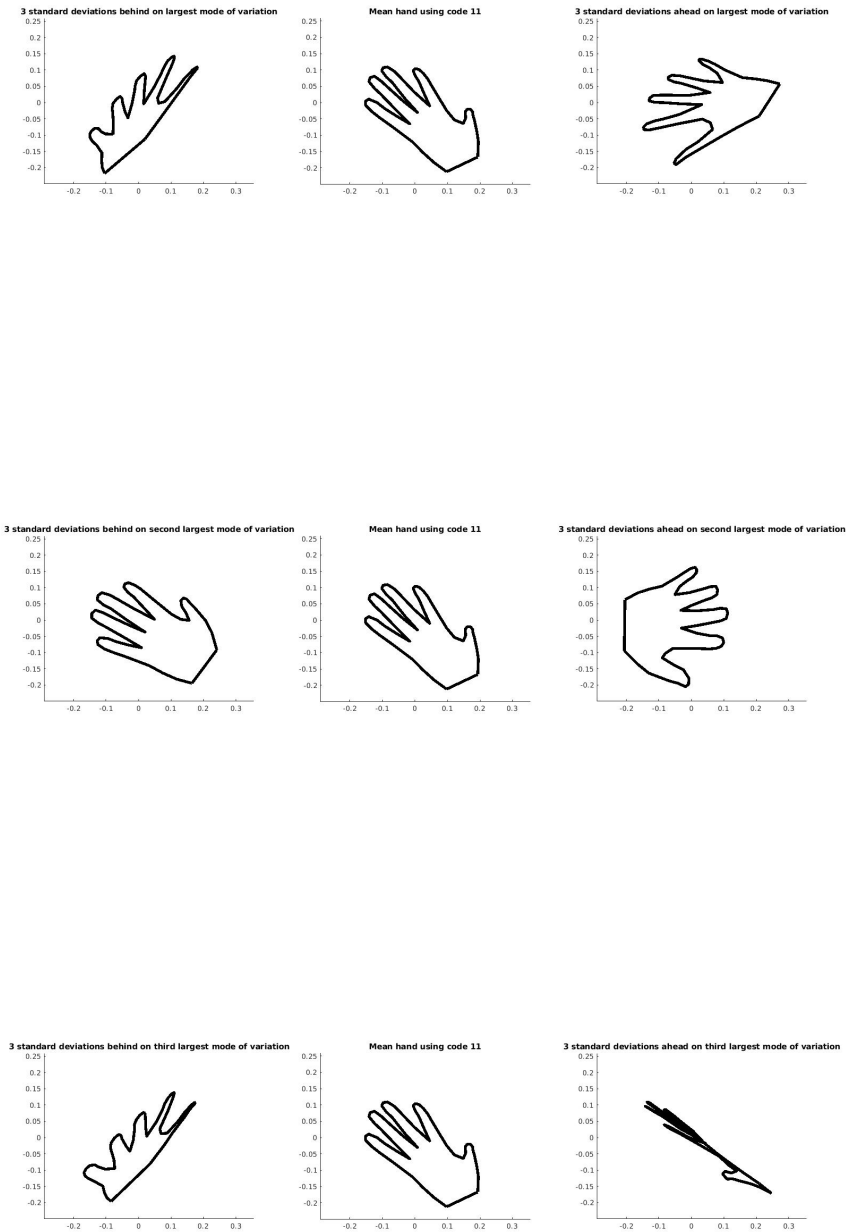


Using Code 22

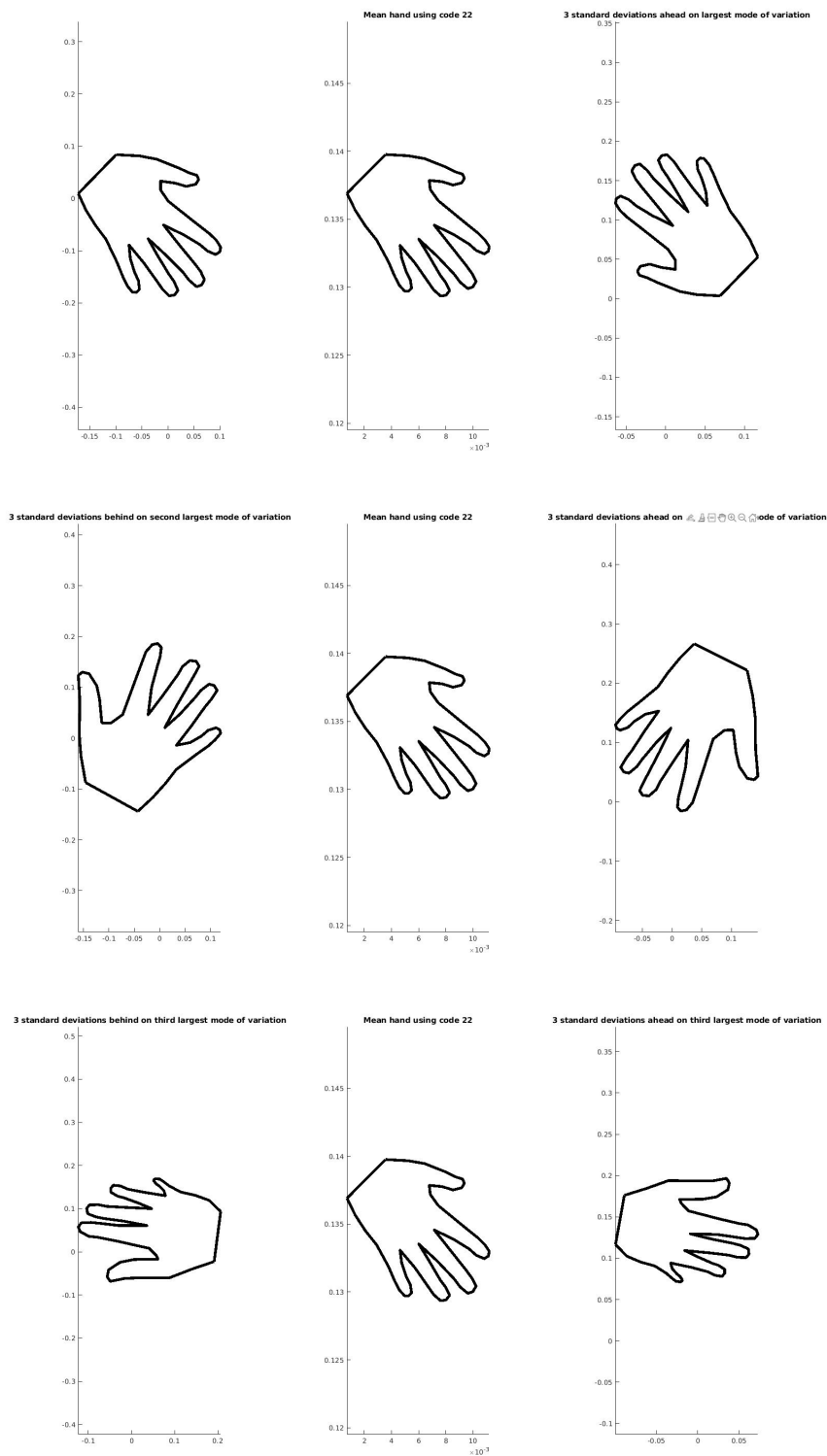


Variance along top 3 directions

Using Code 11



Using Code 22



Question 3

For two shapes z_1, z_2 which are not in pre-shape space, we can first put ~~them~~ the pointset in pre-shape space.

This can be done in two steps:-

1. Standardizing location:-

- Computing centroid of each pointset.
- Subtracting centroid co-ordinates from each point co-ordinate.

$$Z_1 = z_1 - \frac{\sum_{n=1}^N z_{1,n}}{N}$$

Each z_i is a pointset : $\{z_{i,n} \text{ in } \mathbb{R}^2 : n=1, \dots, N\}$

2. Standardizing scale:-

- Re-scaling each pointset to have same scale.
- Divide by 2-norm of the vector.

$$Z_1 = \frac{Z_1}{\sum_n (\|z_{1,n}\|_2)}$$

3. After this we can align shapes w.r.t rotation, by multiplying the pointset with a rotation matrix R .

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Thus the Procrustes distance / dissimilarity between z_1, z_2 with the introduction of transformational, rotational and scale variables as:-

$$d(z_1, z_2) = \min_{O, T, s} d^2(z_1, \text{similarity Transform}(z_2; O, T, s))$$

$$= \min_{O, T, s} \sum_{n=1, \dots, N} \|z_{1n} - s M_O z_{2n} - T\|_2^2$$

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Ans 2 → Objective function for k-means clustering for k-partition $S = (S_1, S_2, \dots, S_k)$ of underlying shapes, with non-empty classes can be given as:-

$$w(s) = \sum_{i=1}^k \sum_{x_j \in S_i} \|x_j - \mu_i\|^2$$

Here, ~~instead~~ instead of mean μ_i of class S_i , we have class of shapes with the mean as the mean shape and euclidean distance replaced by Procrustes distance.

$$w(s) = \sum_{i=1}^k \sum_{z_j \in S_i} d(z_j, \mu_i)$$

$$= \sum_{i=1}^k \sum_{z_j \in S_i} \min_{O, T, S} \| \cdot \|$$

$$w(s) = \sum_{i=1}^k \sum_{z_j \in S_i} \min_{O, T, S} \sum_{n=1, \dots, N} \|z_{jn} - S \mu_i - T\|_2^2$$

Here, for each class S_i and given shape z_j mean μ_i can be found using the following algorithm (discussed in class):-

$$\text{Minimize: } \sum_{m=1, \dots, M} \sum_{n=1, \dots, N} \| \mu_{in} - S_m R_m Z_{mn} - T_m \|^2$$

→ Given mean, find optimal transformation.

→ Given all transformations, find optimal mean pointset. → Average all (aligned) pointsets.

Ans 3. Algorithm for clustering (k-Means++):-

→ An initial estimate for the k-class mean shape is given

(i) → Given representatives μ_i , we minimize objective function $w(s)$ with respect to S , assigning each shape z_i to the class whose mean-shape has the minimum Procrustes distance to it.

(ii) → Given class label S , we minimize with respect to the mean-shape of class μ_i for $i=1, \dots, k$ by finding the mean of shapes z_i in S_i , using algo mentioned in part (b).

→ Repeat (i) and (ii) until convergence.

Termination condition:- If $w(s)$ doesn't decrease from its value from previous estimate to the updated estimate, then terminate.

Initialization condition:-

pick a shape z uniformly at random and set $T \leftarrow \{z\}$

while $|T| < k$:

pick $z \in Z$ at random, with probability proportional to $\text{cost}(z, T) = \min_{\mu \in T} d(z, \mu)$

$T \leftarrow T \cup \{z\}$