

Part 2: Lack of Optimality of K-means

The dataset is:

$$x_1 = 1, x_2 = 2, x_3 = 3, x_4 = 4$$

We use $K=2$, and initialize centroids as:

$$\mu_1 = 2, \mu_2 = 4$$

Iteration 1: Assign points to nearest centroids

Distance of $x_1 = 1$: $|1-2|=1, |1-4|=3 \rightarrow$ assign to μ_1

Distance of $x_2 = 2$: $|2-2|=0, |2-4|=2 \rightarrow$ assign to μ_1

Distance of $x_3 = 3$: $|3-2|=1, |3-4|=1 \rightarrow$ Tie, assign to smaller index, so assign to μ_1

Distance of $x_4 = 4$: $|4-2|=2, |4-4|=0 \rightarrow$ assign to μ_2

Thus:

$$C_1 = \{1, 2, 3\}, C_2 = \{4\}$$

Iteration 2: Update centroids

- For cluster $C_1 = \{1, 2, 3\}$: new centroid = $\frac{1+2+3}{3} = 2$
- For cluster $C_2 = \{4\}$: new centroid = 4

So centroids remain:

$$\mu_1 = 2, \quad \mu_2 = 4$$

This is a stable solution (no change in assignments)

Distortion for this clustering

$$J = (1-2)^2 + (2-2)^2 + (3-2)^2 + (4-4)^2 = 1+0+1+0=2$$

But is this globally optimal?

consider another partition:

$$C_1 = \{1, 2\}, \quad C_2 = \{3, 4\}$$

• centroids: $\mu_1 = 1.5, \mu_2 = 3.5$

• Distortion:

$$(1-1.5)^2 + (2-1.5)^2 + (3-3.5)^2 + (4-3.5)^2 = 0.25 + 0.25 + 0.25 + 0.25 = 1$$

This is smaller than the $J=2$ we got before

Explanation:

Since $J = 1 < J_{\text{conv}} = 2$, the solution found by k-means (with the given initialization) is not globally optimal.

k-means is an alternating minimization method that guarantees a non-increasing SSE at each step but only convergence to a local fixed point. Starting from $\mu_1 = 2, \mu_2 = 4$, the algorithm converges to the clustering $\{1, 2, 3\}, \{4\}$ with objective value $J_{\text{conv}} = 2$. The tie at x_3 causes it to be assigned to cluster 1, keeping the centroid at 2 and preventing movement to the globally optimal clustering $\{1, 2\}, \{3, 4\}$, which achieves $J = 1$.

This demonstrates that k-means can converge to a suboptimal local solution rather than the global optimum, due to its sensitivity to initialization and the nonconvexity of its objective.