

Hierarchical Clustering

Agreggation criteria

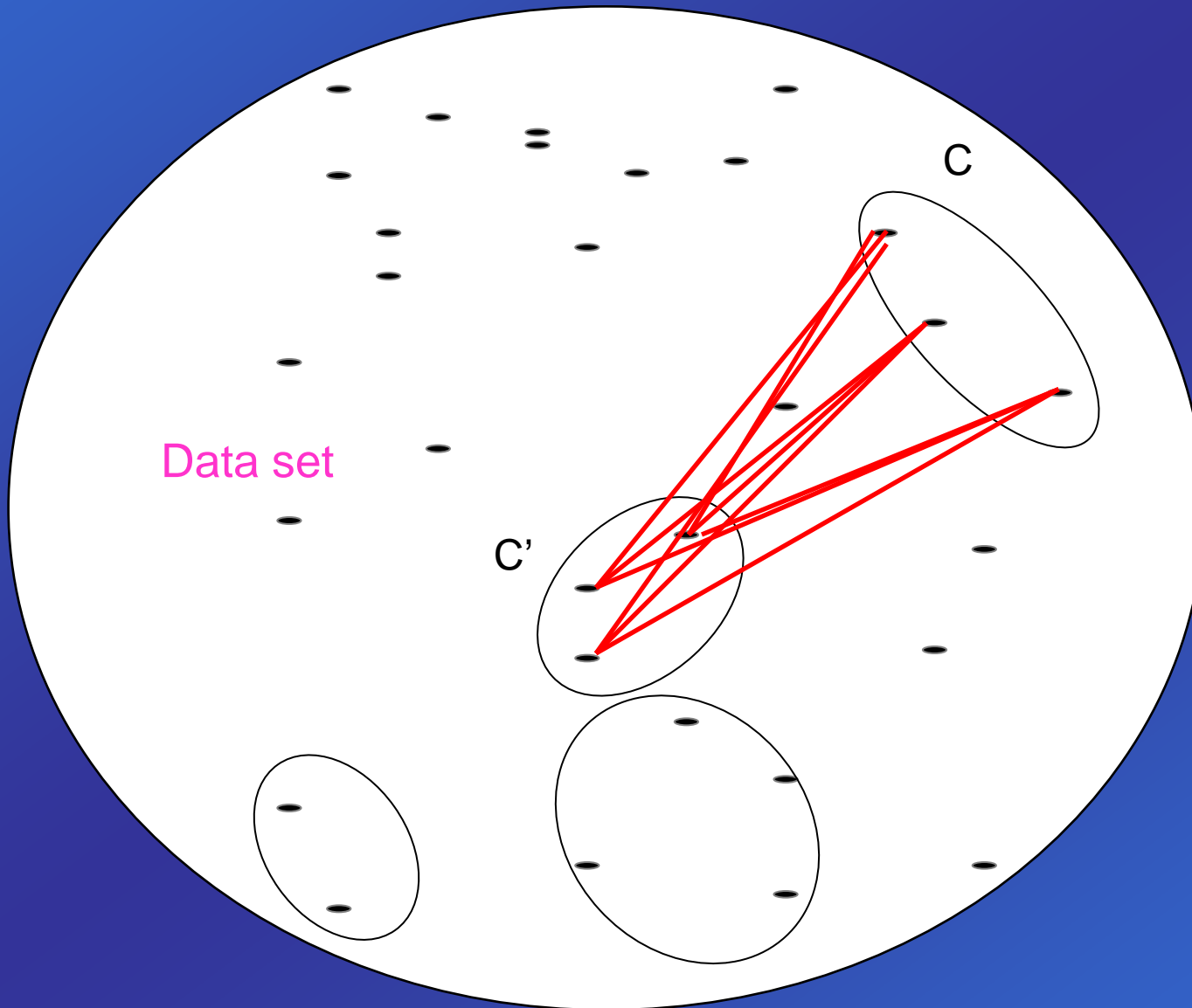
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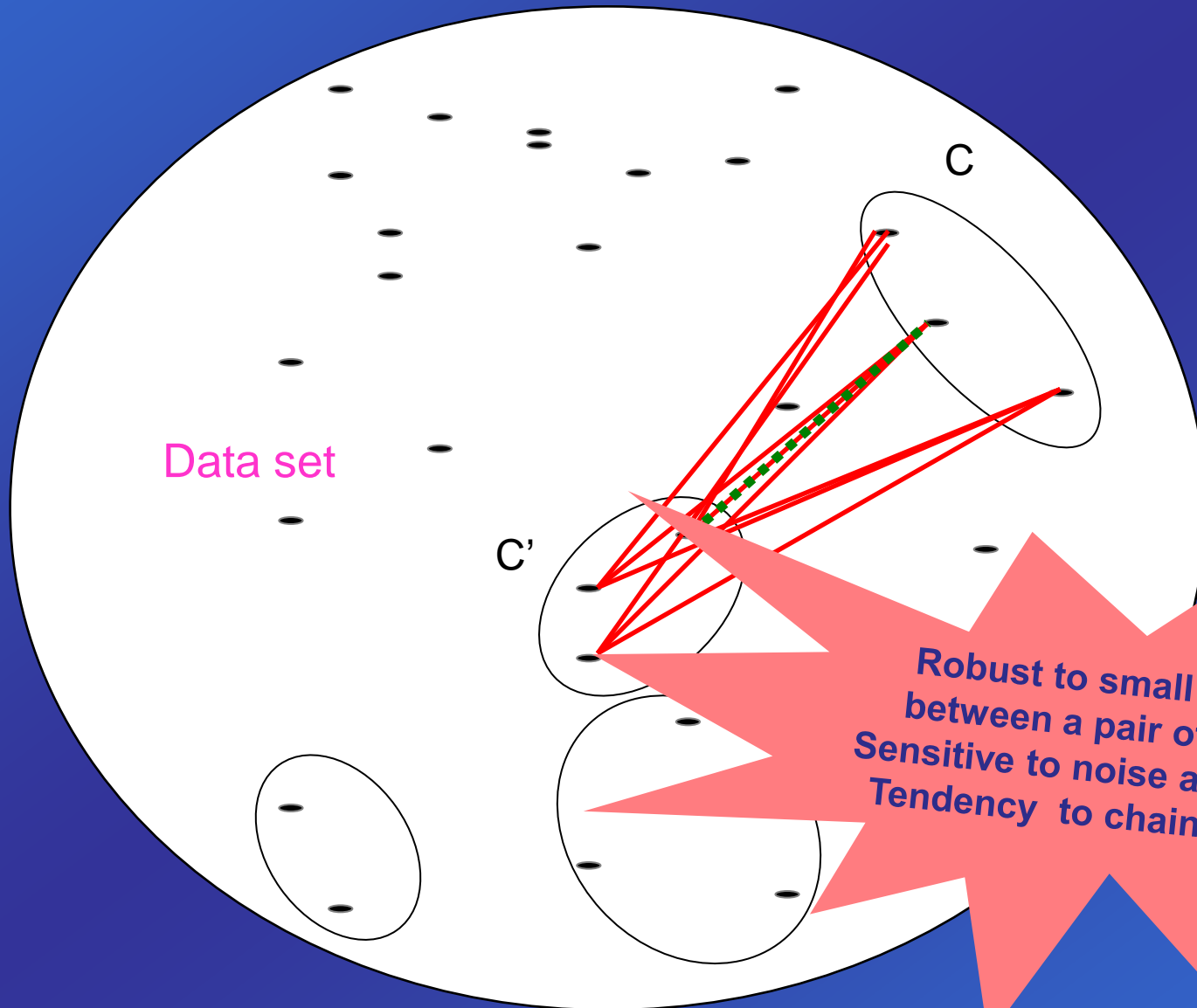
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Aggregation Criteria

$$d(C, C') = f(d(i, i')), i \in C, i' \in C'$$



Single linkage (Sneath 1957) $d(C, C') = \min(d(i, i')), i \in C, i' \in C'$

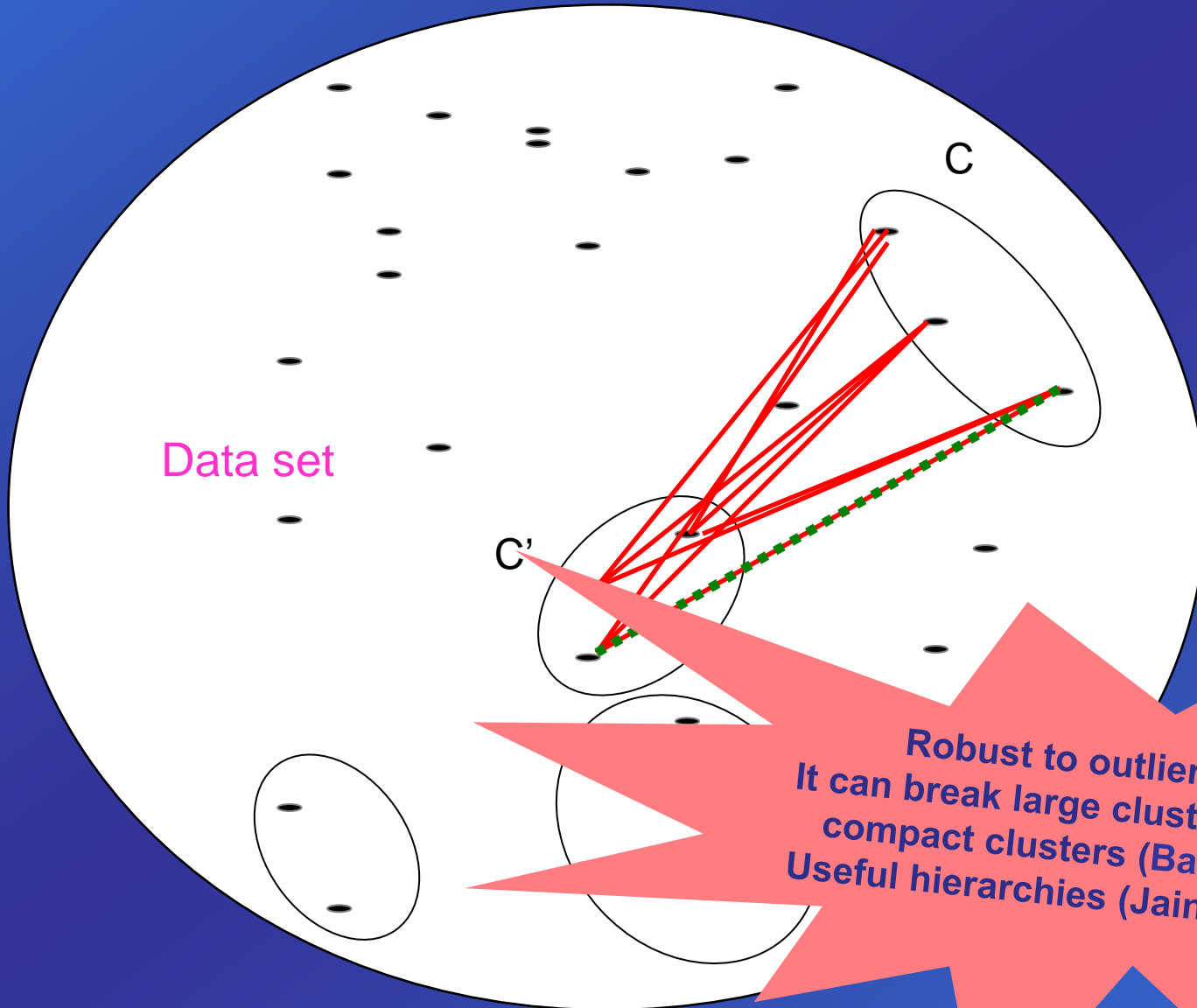


**Robust to small changes
between a pair of objects.
Sensitive to noise and outliers.
Tendency to chaining effect.**

Complete linkage

(Sorensen 1948)

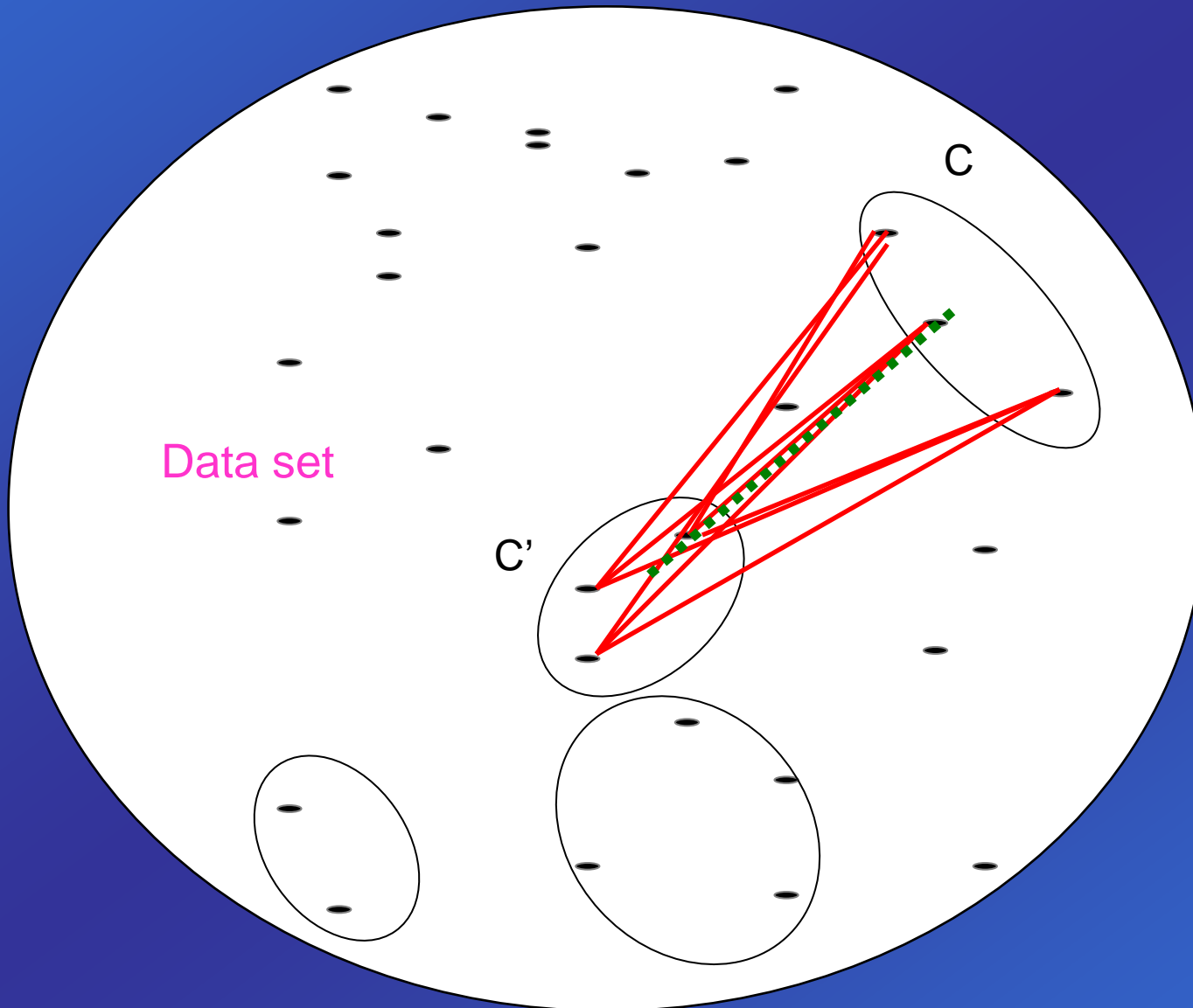
$$d(C, C') = \max(d(i, i')), i \in C, i' \in C'$$



**Robust to outliers and noise.
It can break large clusters. Conservative,
compact clusters (Baeza-Yates 1992).
Useful hierarchies (Jain and Dubes 1998)**

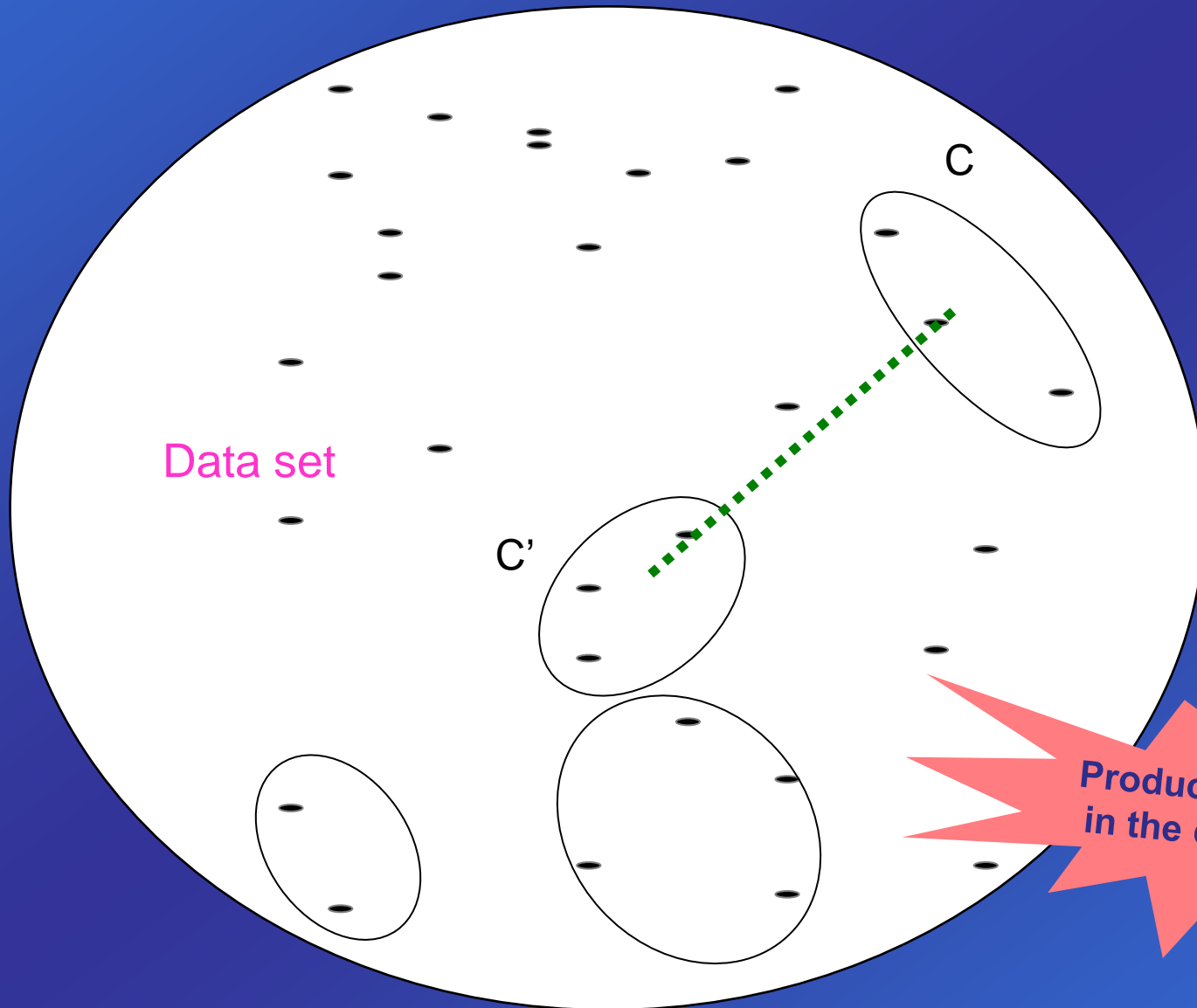
Average linkage

$$d(C, C') = \text{mean}(d(i, i')), i \in C, i' \in C'$$



Centroid

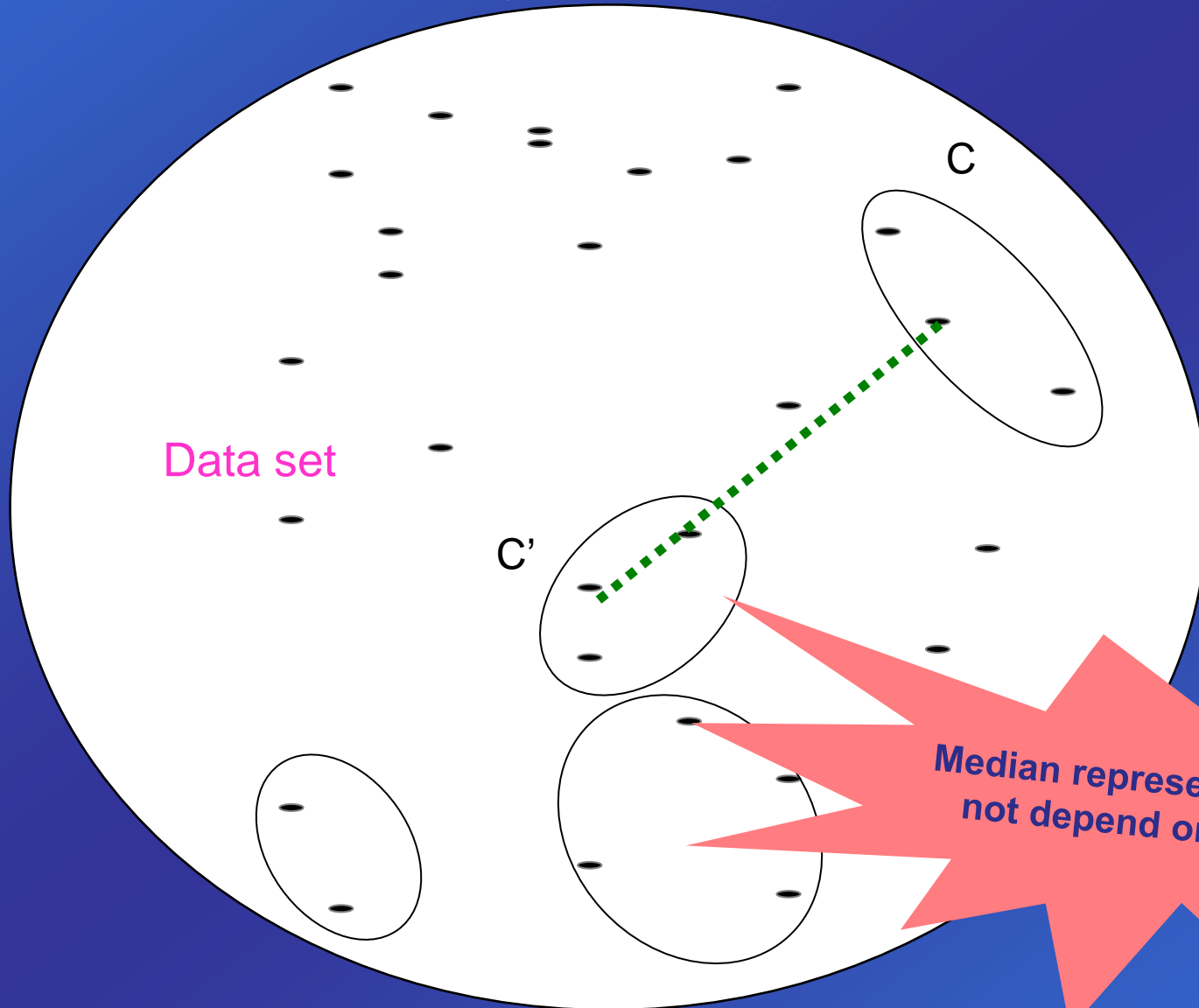
$d(C, C') = d(c, c')$, c, c' centroids



**Produce inversions
in the dendrogram**

Median linkage

$d(C, C') = d(c, c')$, c, c' centroids
(Gower 1967)



**Median representativeness do
not depend on cluster size**

Ward's method (Ward 1963)

- Ascendant hierarchical method
- Group the two classes giving minimal inter-class inertia loss

- Inertia (physical concept)

$$M^2(\mathcal{I}/\bar{\mathbf{i}}) = \sum_{i \in \mathcal{I}} m_i d^2(i, \bar{\mathbf{i}})$$

- Huygens theorem

$$M^2(\mathcal{I}/\bar{\mathbf{i}}) = Mi_{\mathcal{P}}^2(\mathcal{I}/\bar{\mathbf{i}}) + Me_{\mathcal{P}}^2(\mathcal{I}/\bar{\mathbf{i}}),$$

$$Mi_{\mathcal{P}}^2(\mathcal{I}/\bar{\mathbf{i}}) = \sum_{C \in \mathcal{P}} M^2(C/\bar{\mathbf{i}}_C) = \sum_{C \in \mathcal{P}} \sum_{i \in C} m_i d^2(i, \bar{\mathbf{i}}_C)$$

$$Me_{\mathcal{P}}^2(\mathcal{I}/\bar{\mathbf{i}}) = \sum_{C \in \mathcal{P}} m_C d^2(\bar{\mathbf{i}}_C, \bar{\mathbf{i}})$$

- Every aggregation increases intra-class inertia with

$$\Delta_{\xi} = Mi_{\mathcal{P}_{\xi+1}}^2(\mathcal{I}/\bar{\mathbf{i}}) - Mi_{\mathcal{P}_{\xi}}^2(\mathcal{I}/\bar{\mathbf{i}}) = m_{C_e} d^2(C_e, \bar{\mathbf{i}}_C) + m_{C_d} d^2(C_d, \bar{\mathbf{i}}_C)$$

Minimize

- Inertia related with quantity of information (Thm Benzecri 1973)

The more informative, more inertia

**Interpretable
classes**

variability

The more variable, more inertia

- Quite popular

**Can exaggerate number of
Exception-classes**