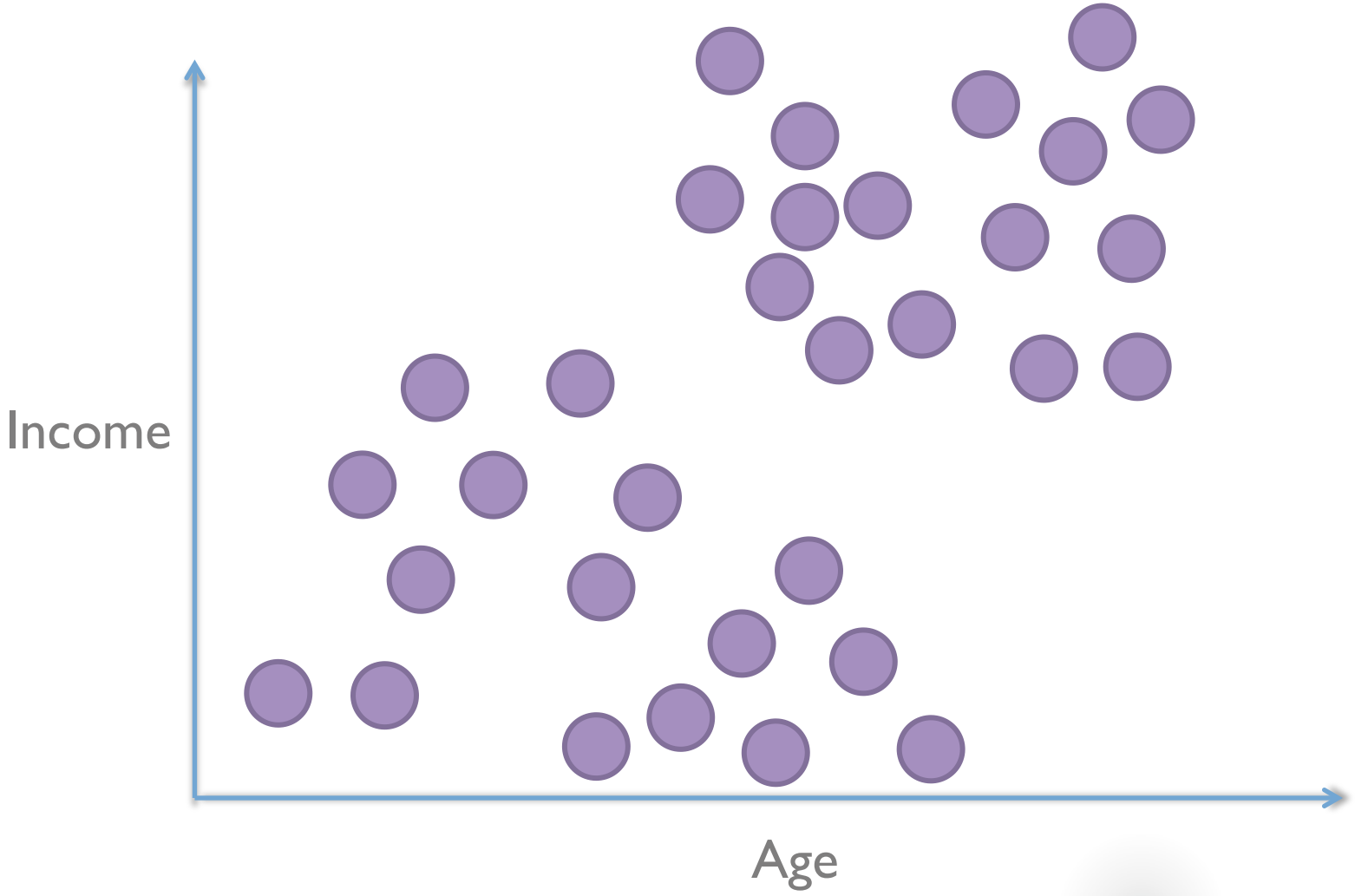
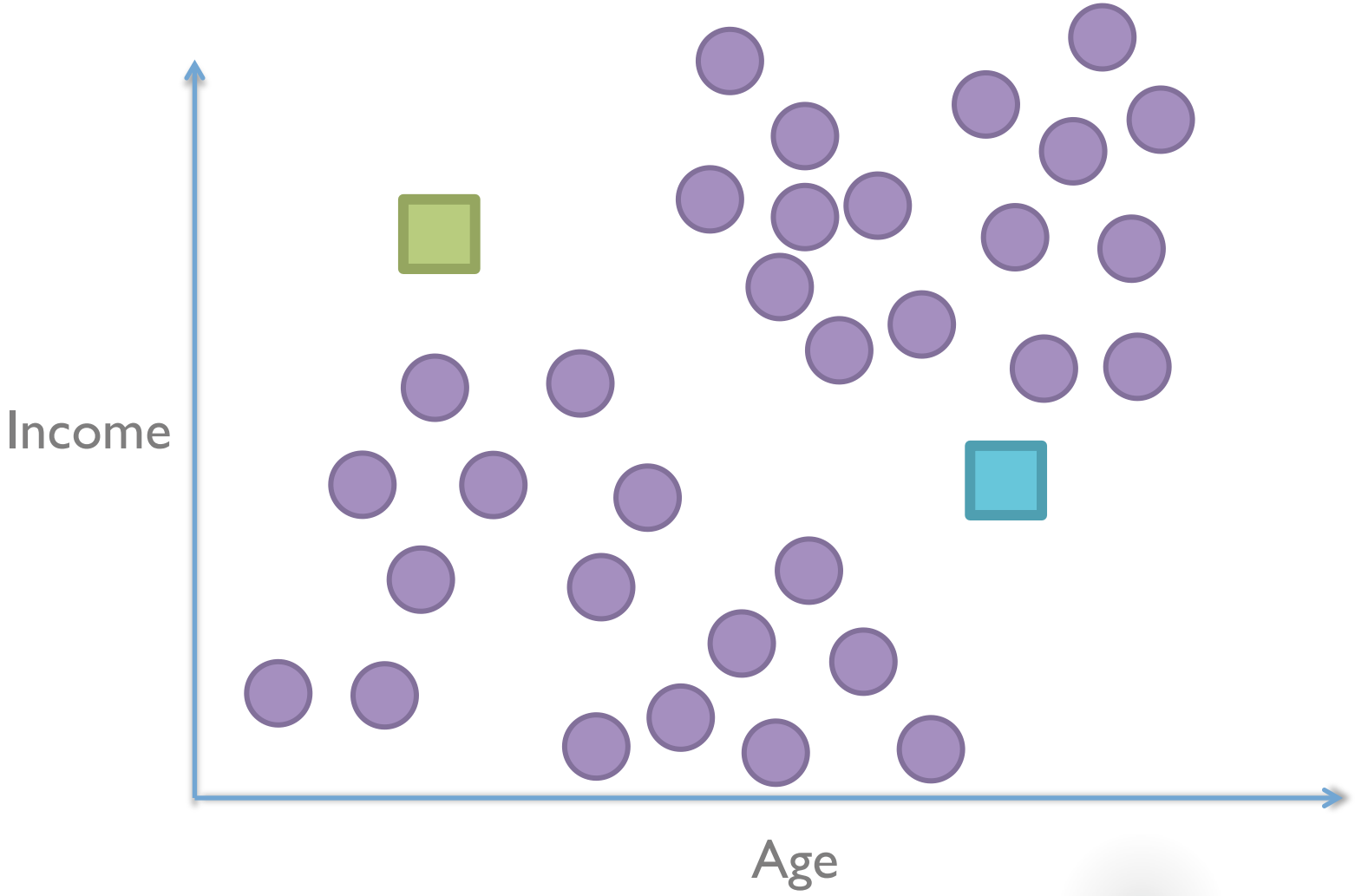
Other Clustering Algorithms

Remember K--Means?



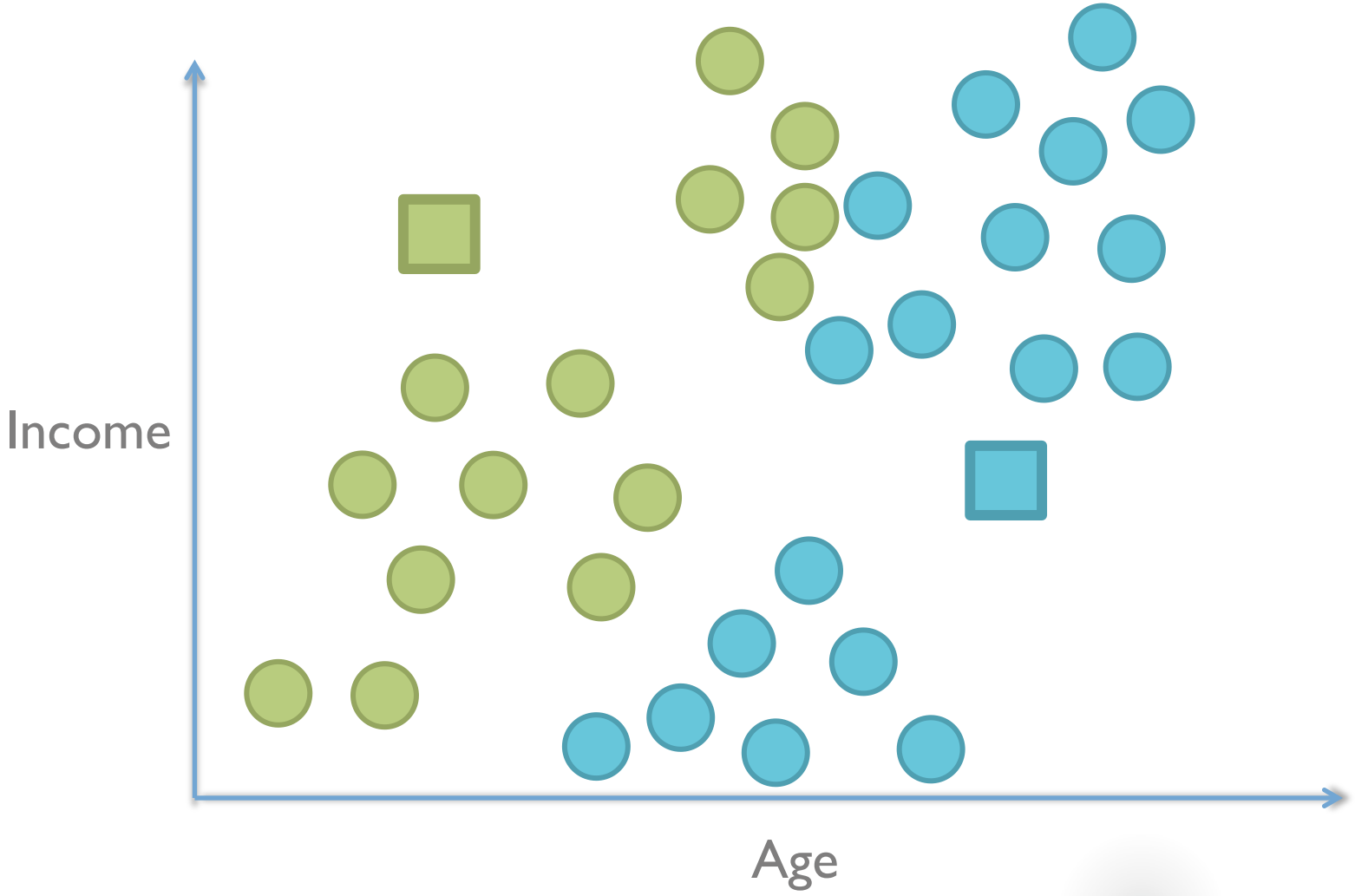
K-Means K=2

Randomly assign two cluster centers



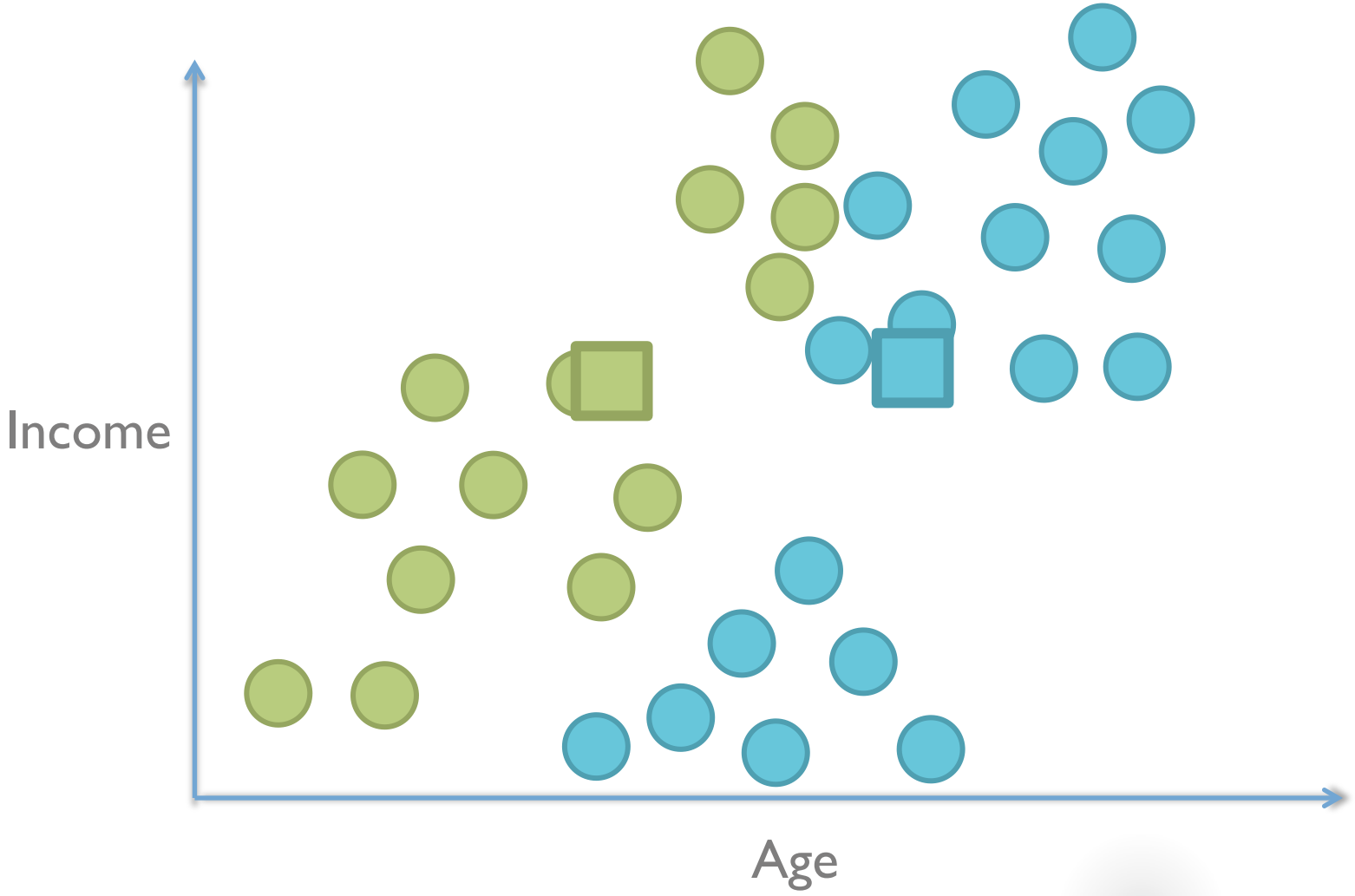
K--Means K=2

Each point belongs to closest center



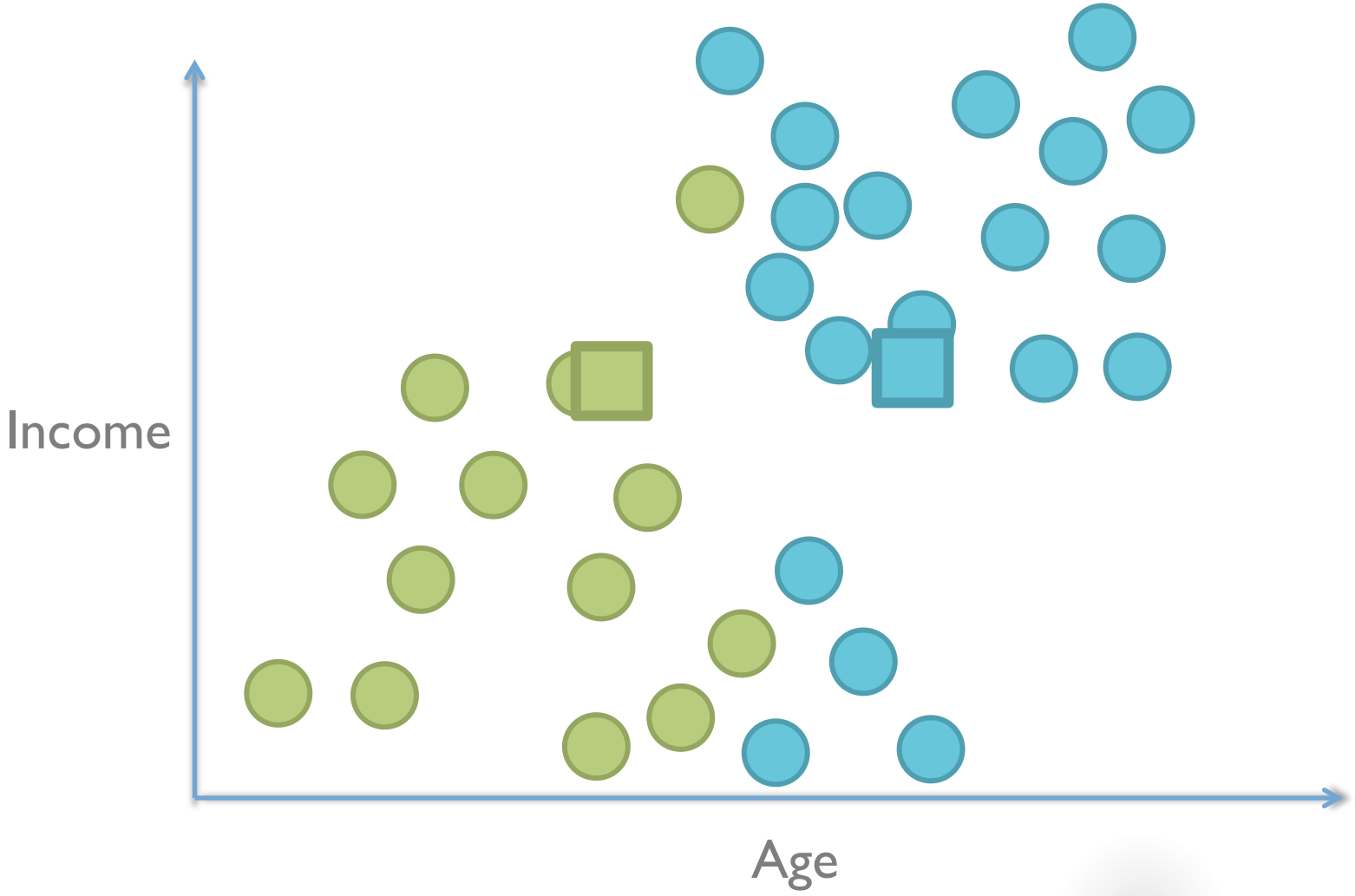
K-Means K=2

Move each center to the cluster's mean



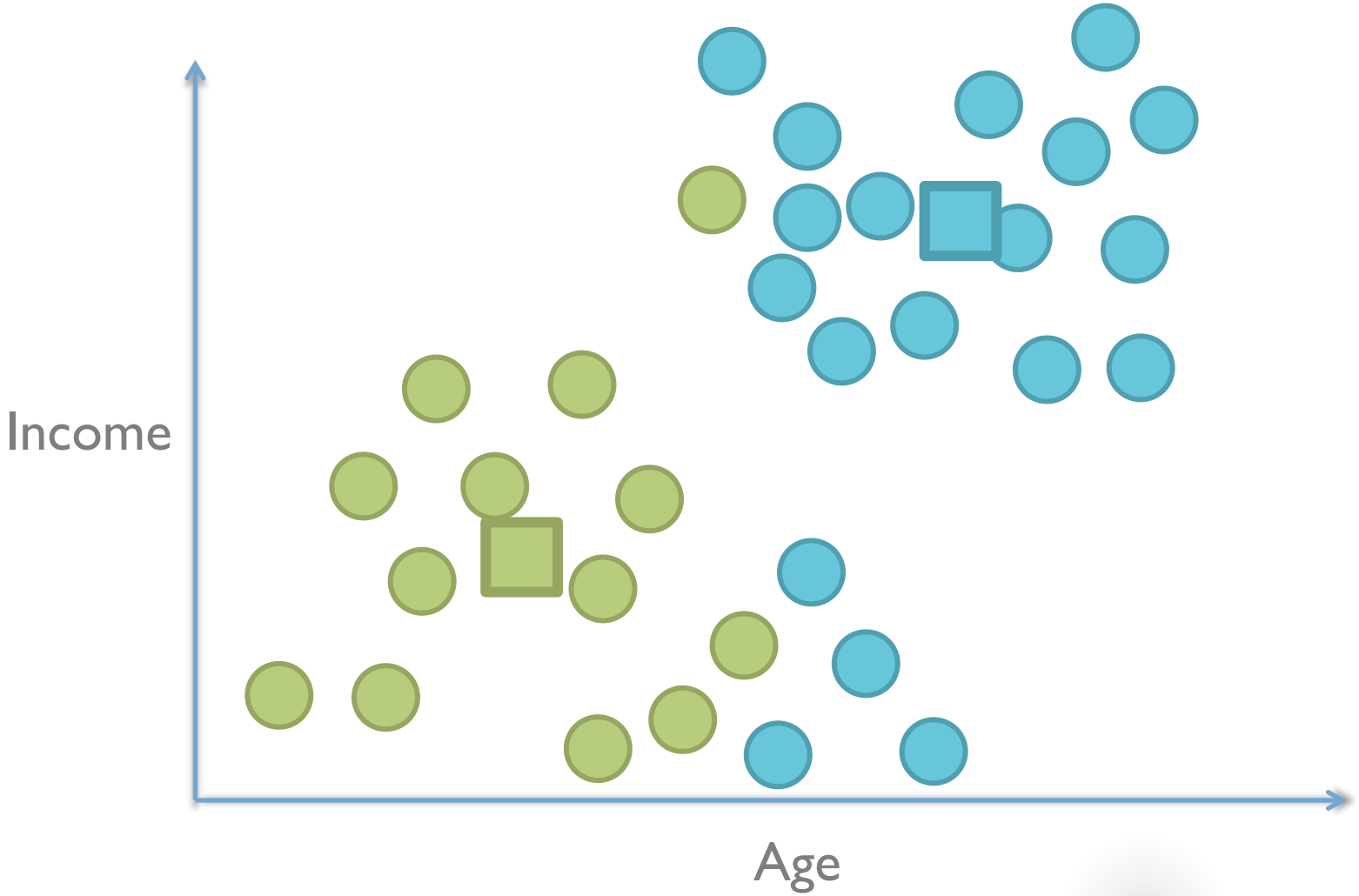
K--Means K=2

Each point belongs to the closest center



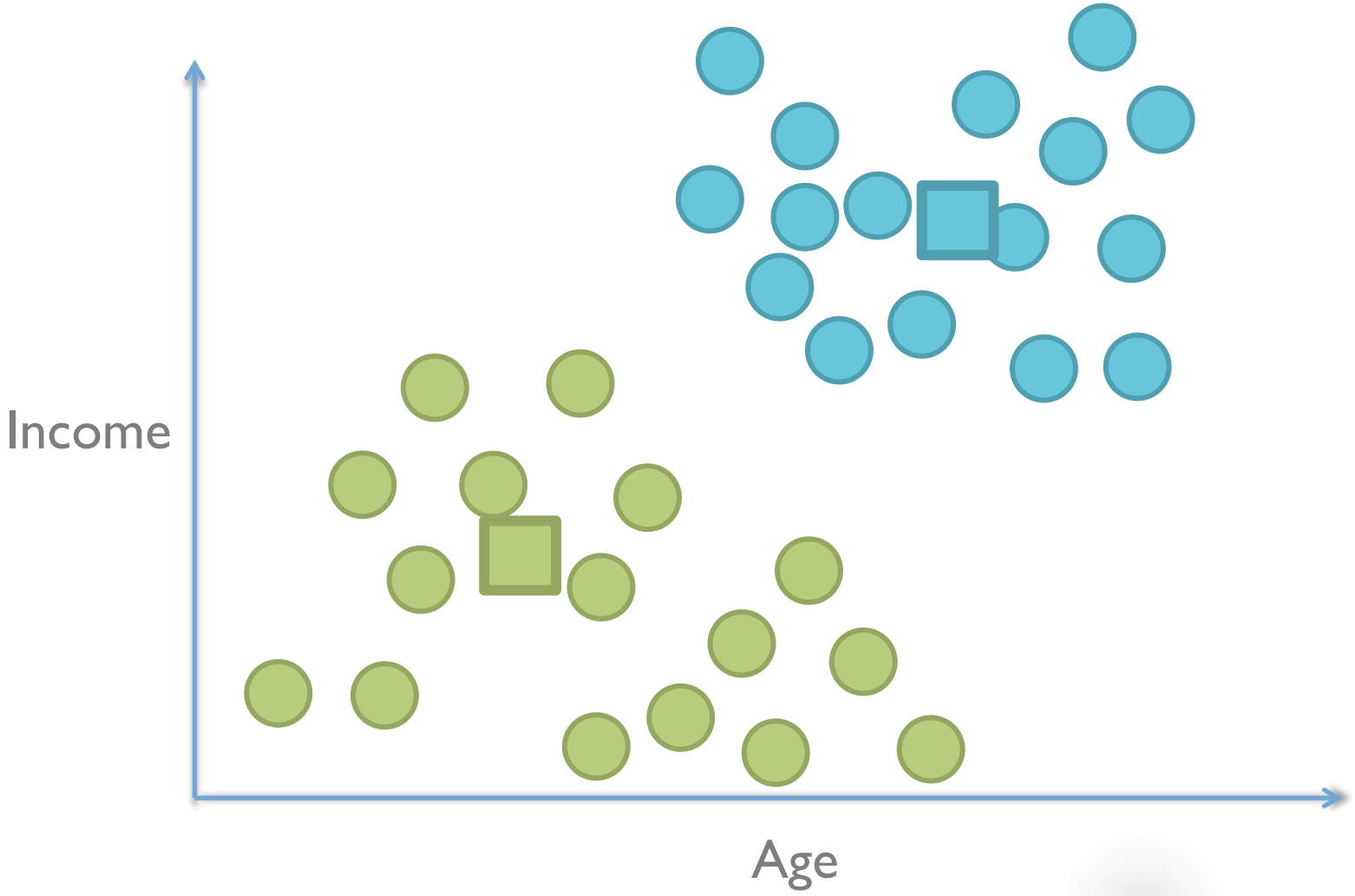
K--Means K=2

Move each center to the cluster's mean



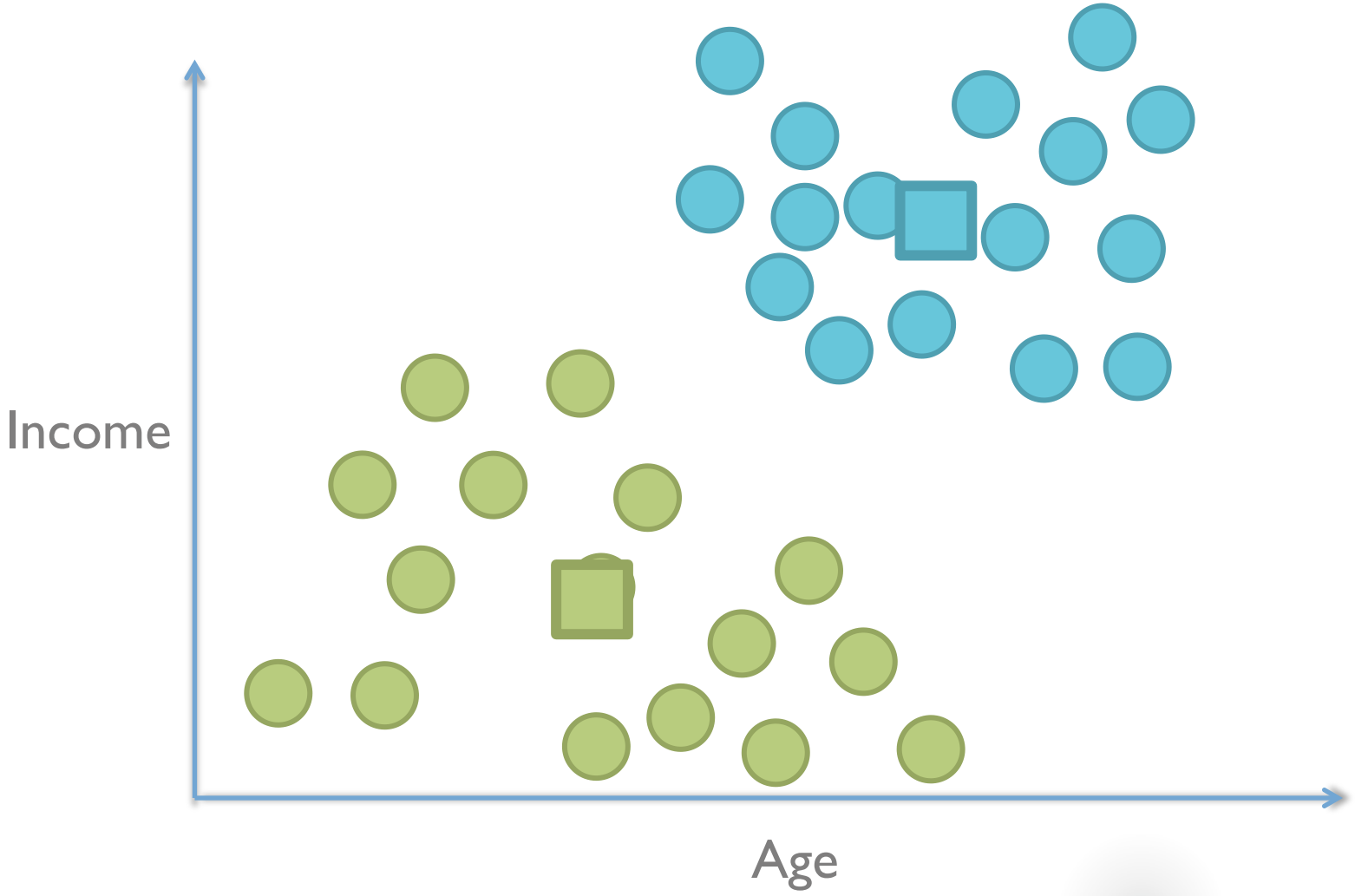
K--Means K=2

Each point belongs to closest center



K--Means K=2

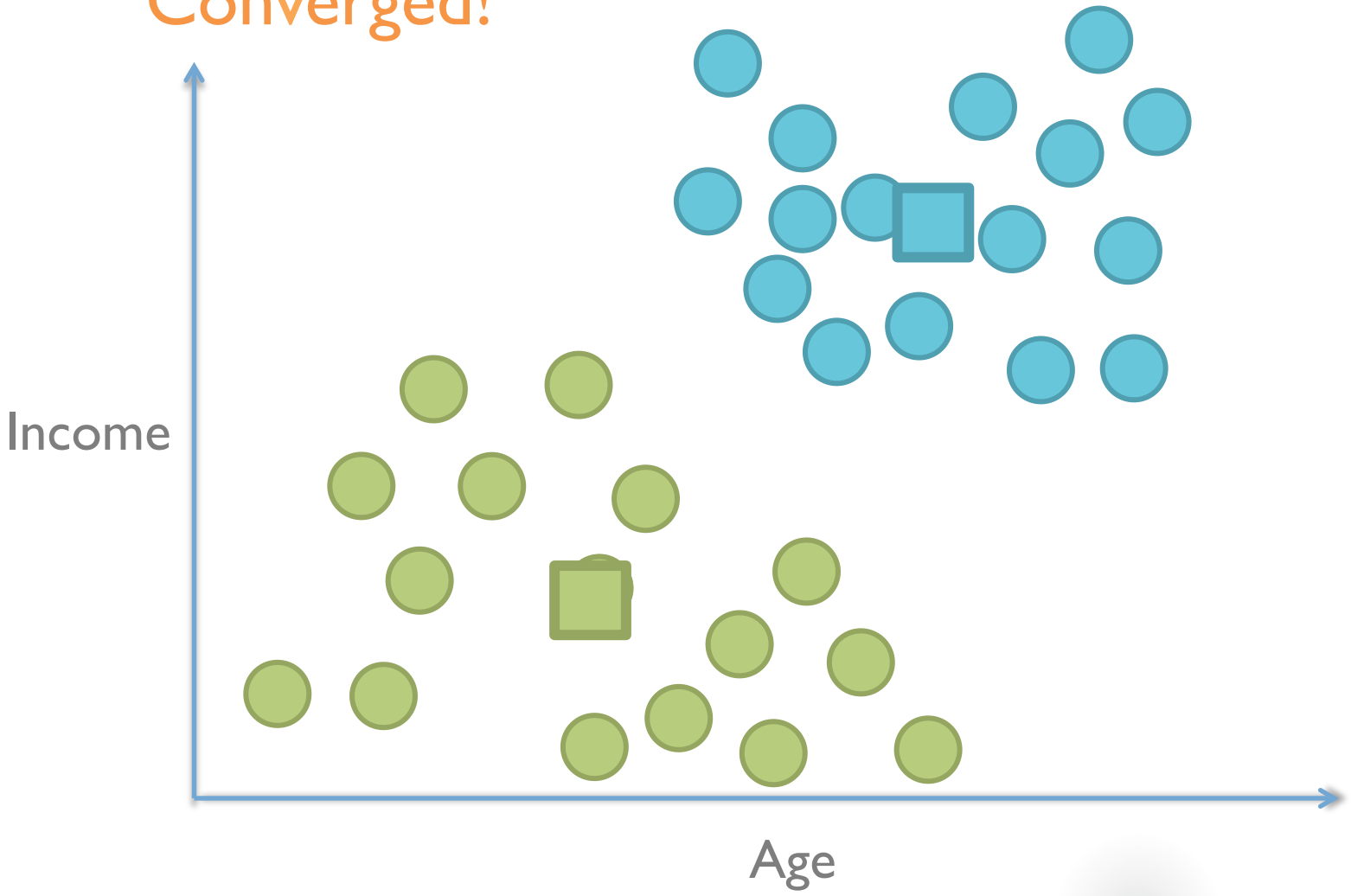
Move each center to the cluster's mean



K-Means K=2

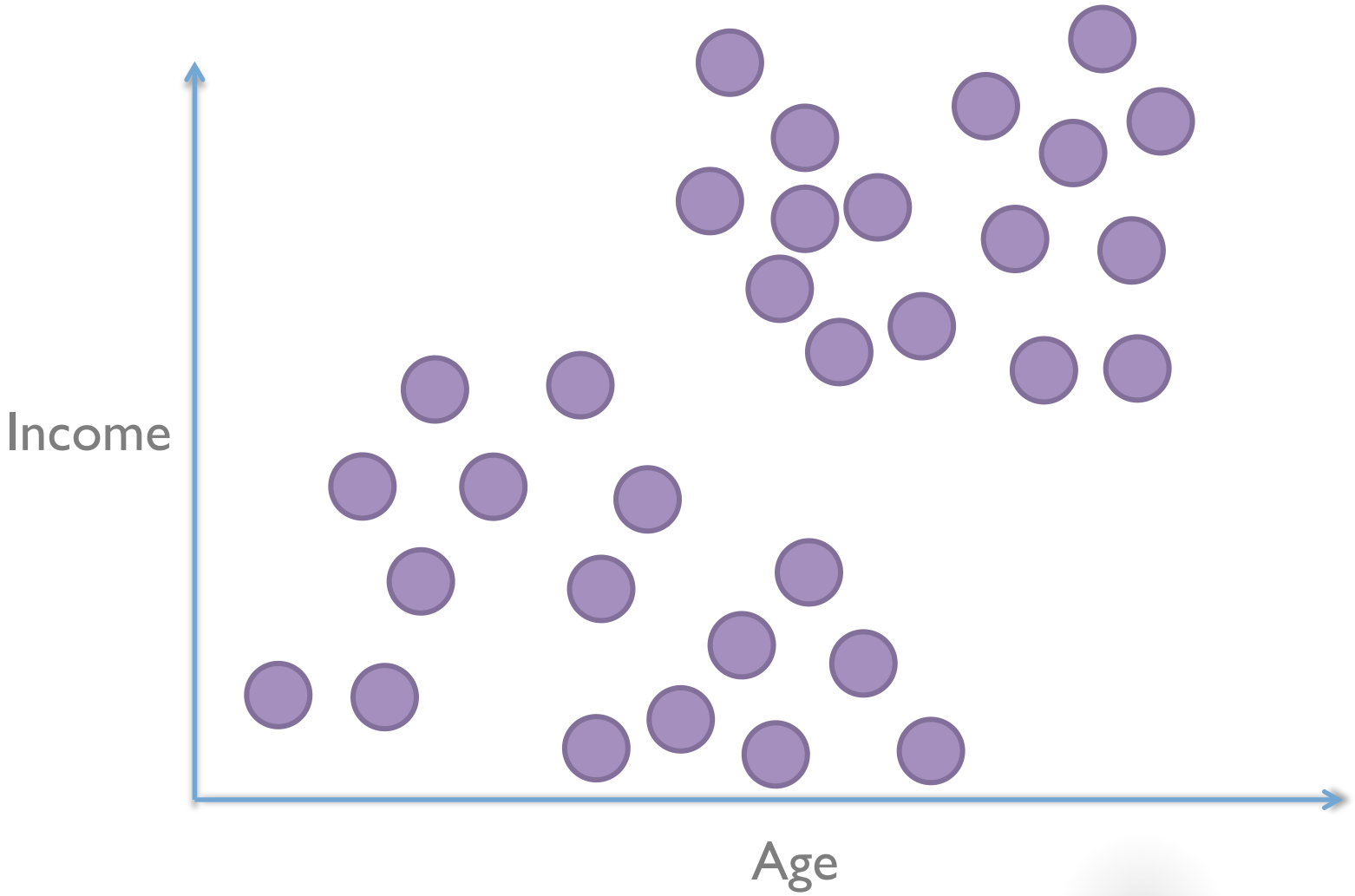
Points don't change anymore.

Converged!



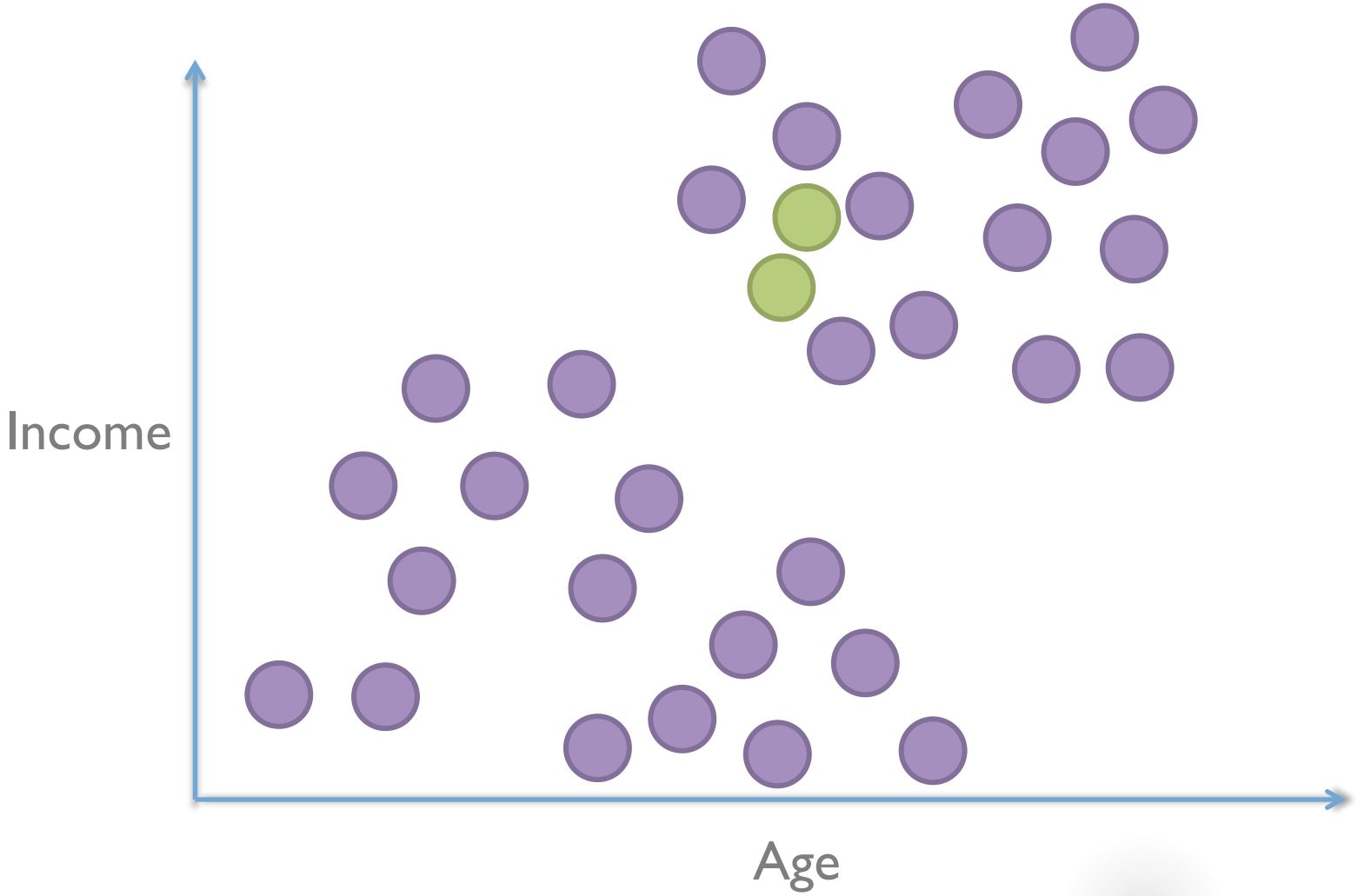
Hierarchical Agglomerative Clustering

Hierarchical Agglomerative Clustering



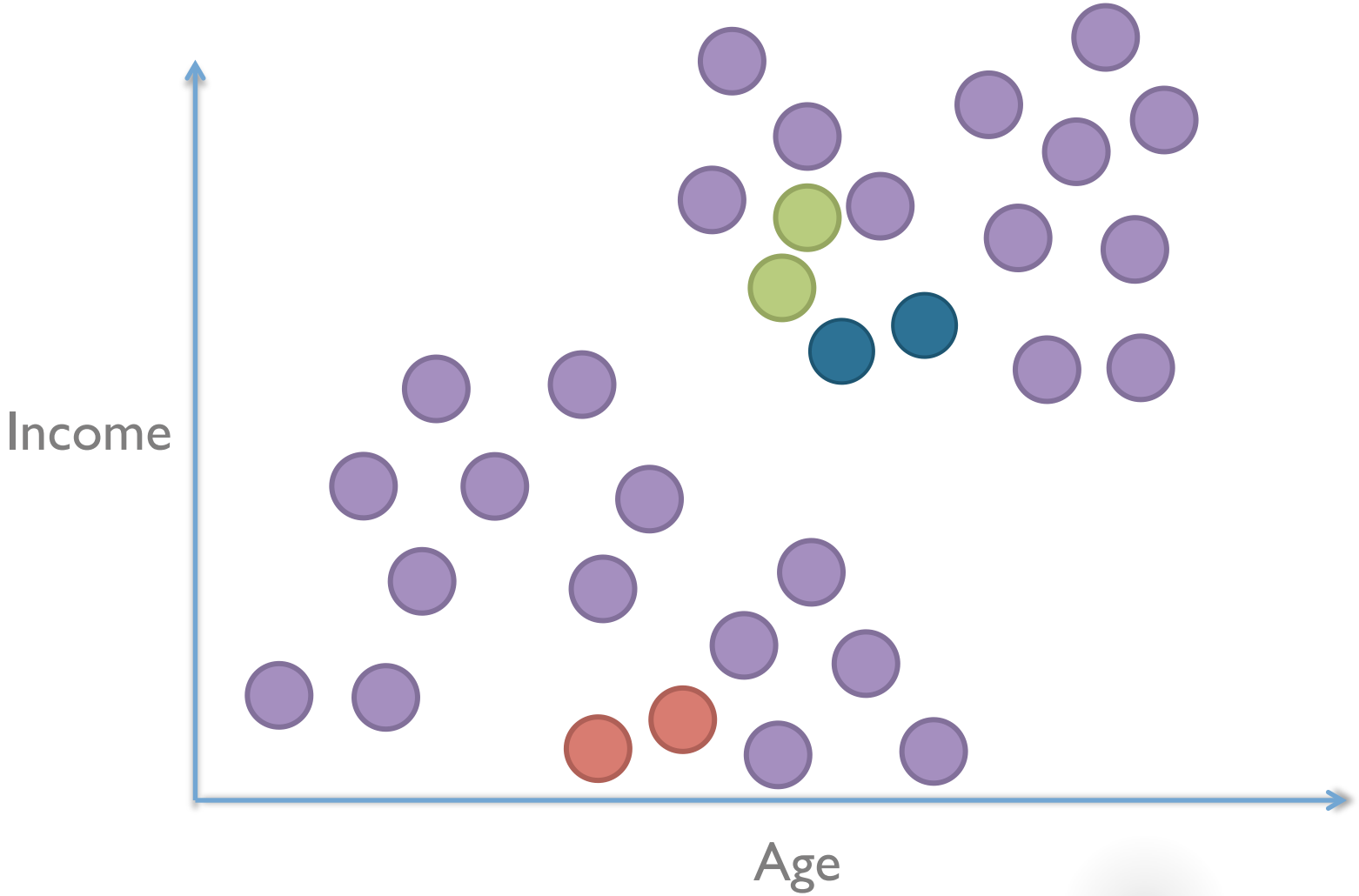
Agglomerative Hierarchical Clustering

Find closet pair, merge into a cluster



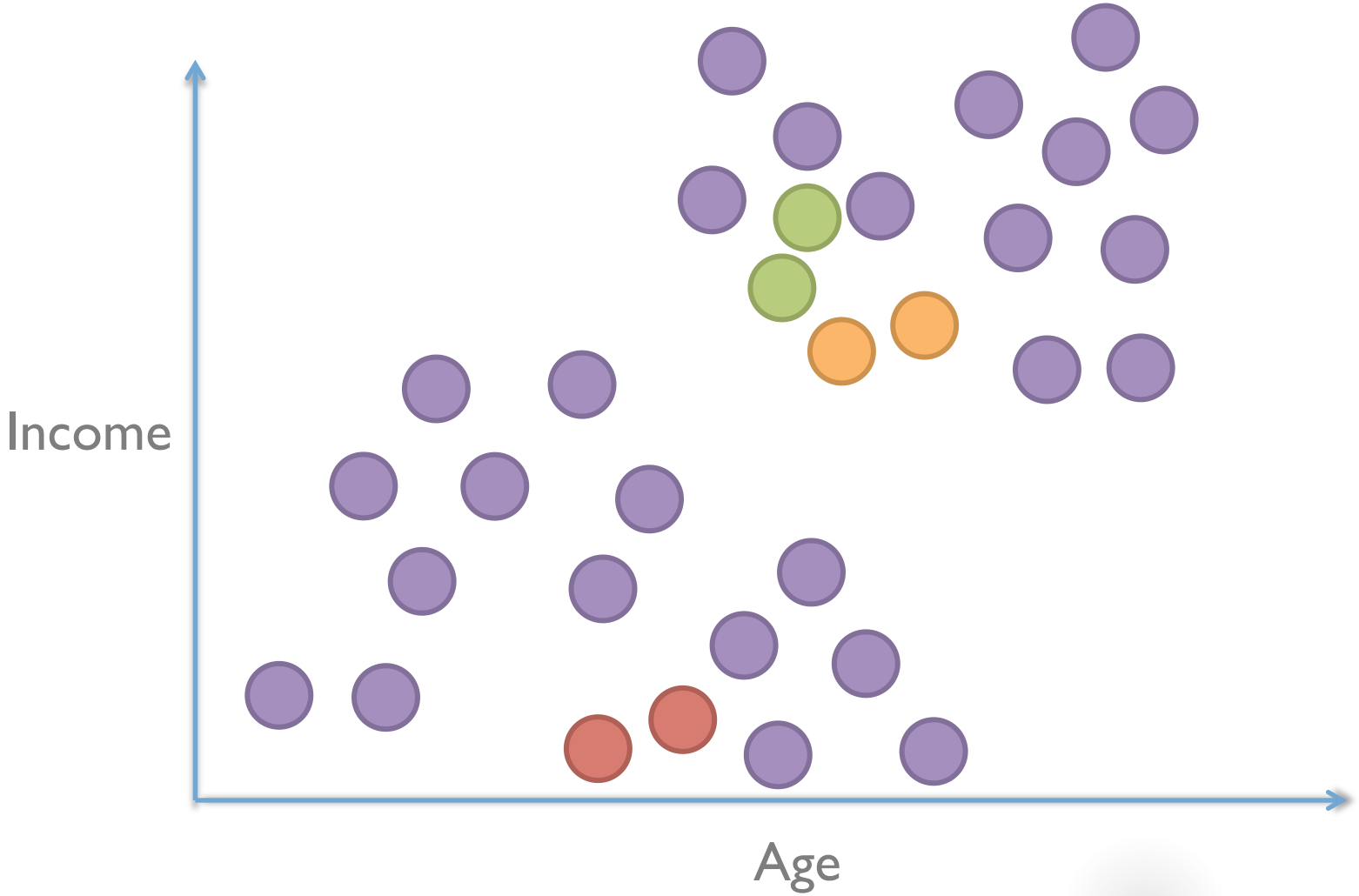
Agglomerative Hierarchical Clustering

Find next closet pair, merge



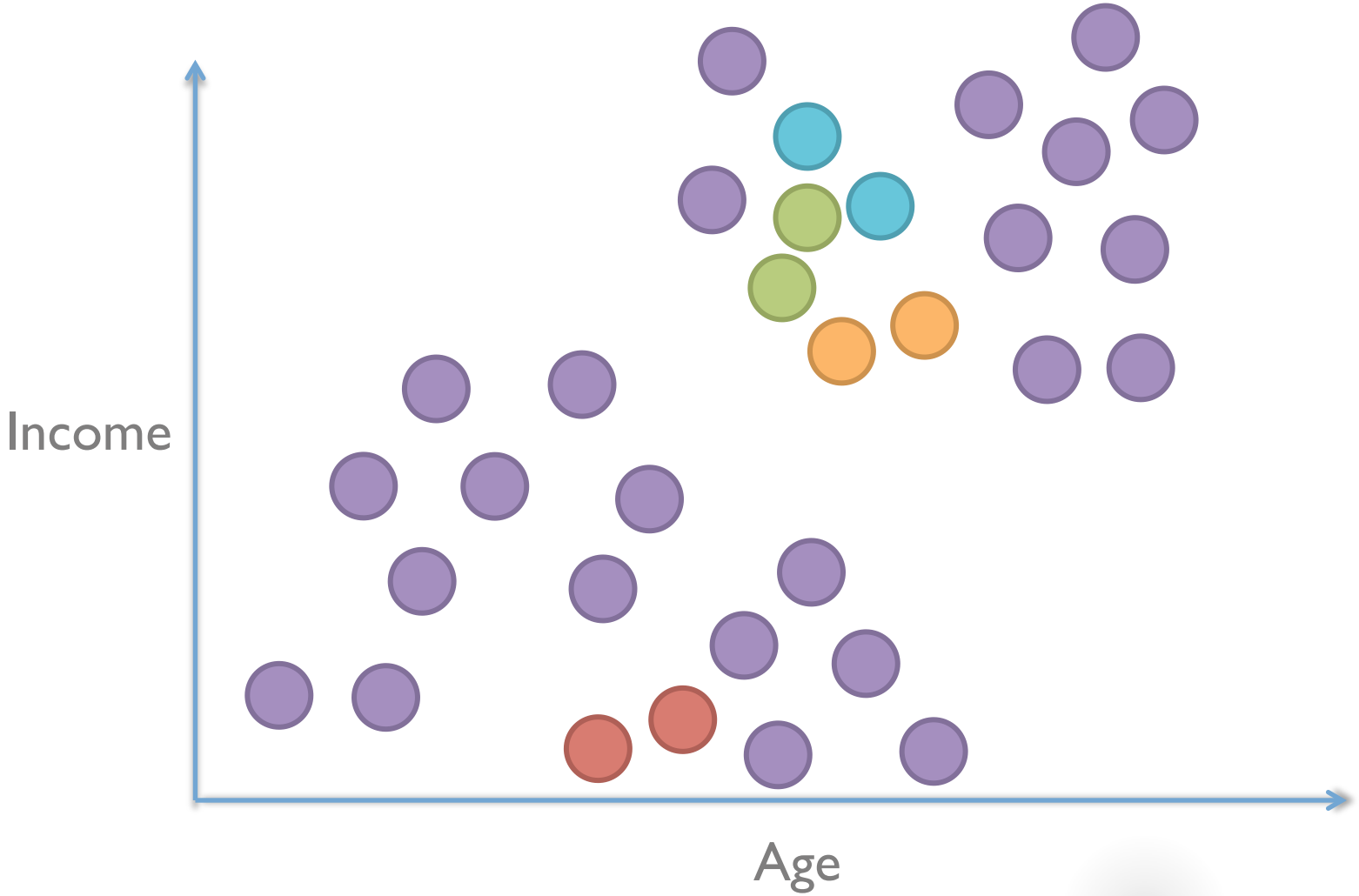
Agglomerative Hierarchical Clustering

Find next closet pair, merge



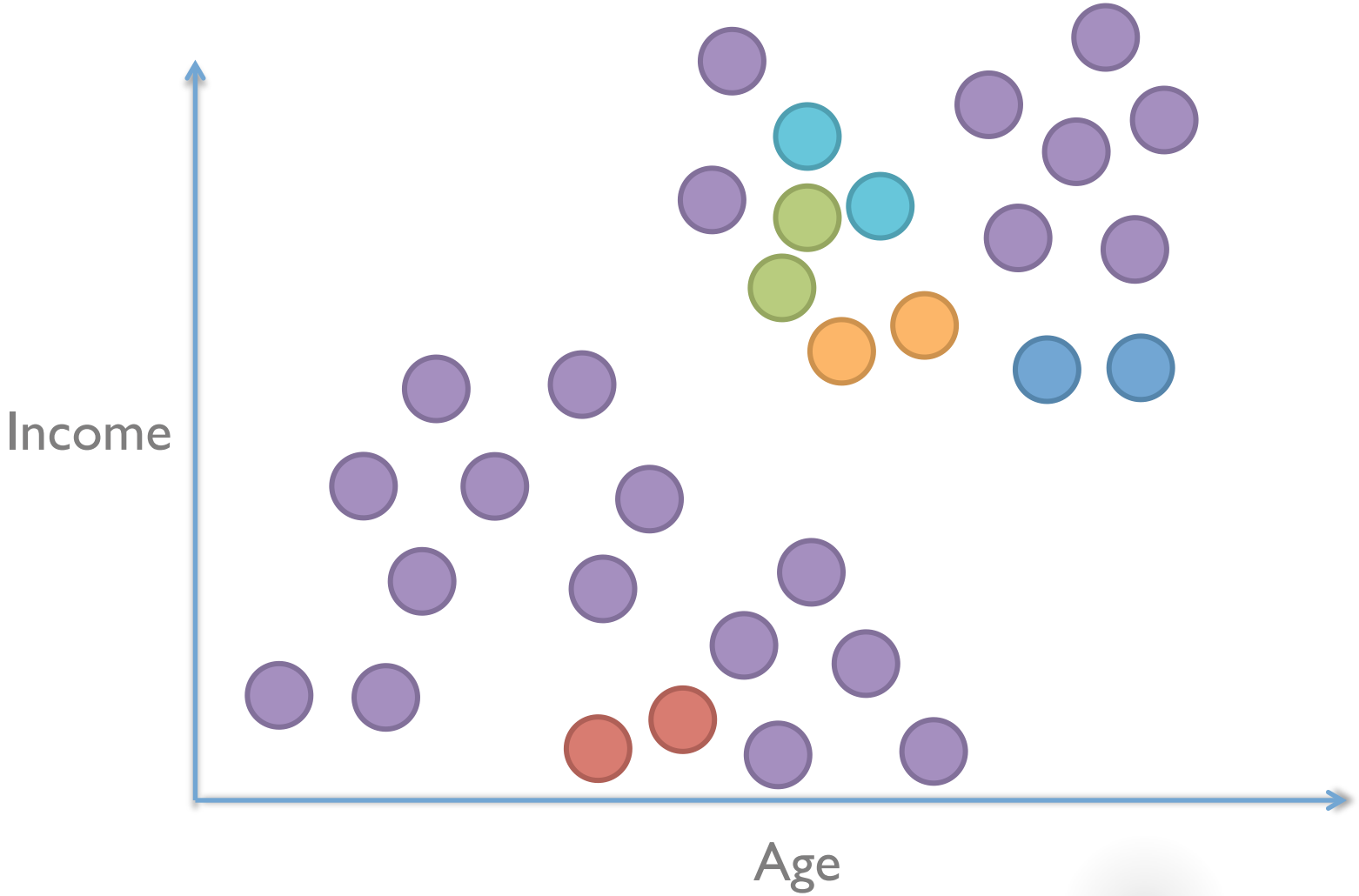
Agglomerative Hierarchical Clustering

Find next closet pair, merge



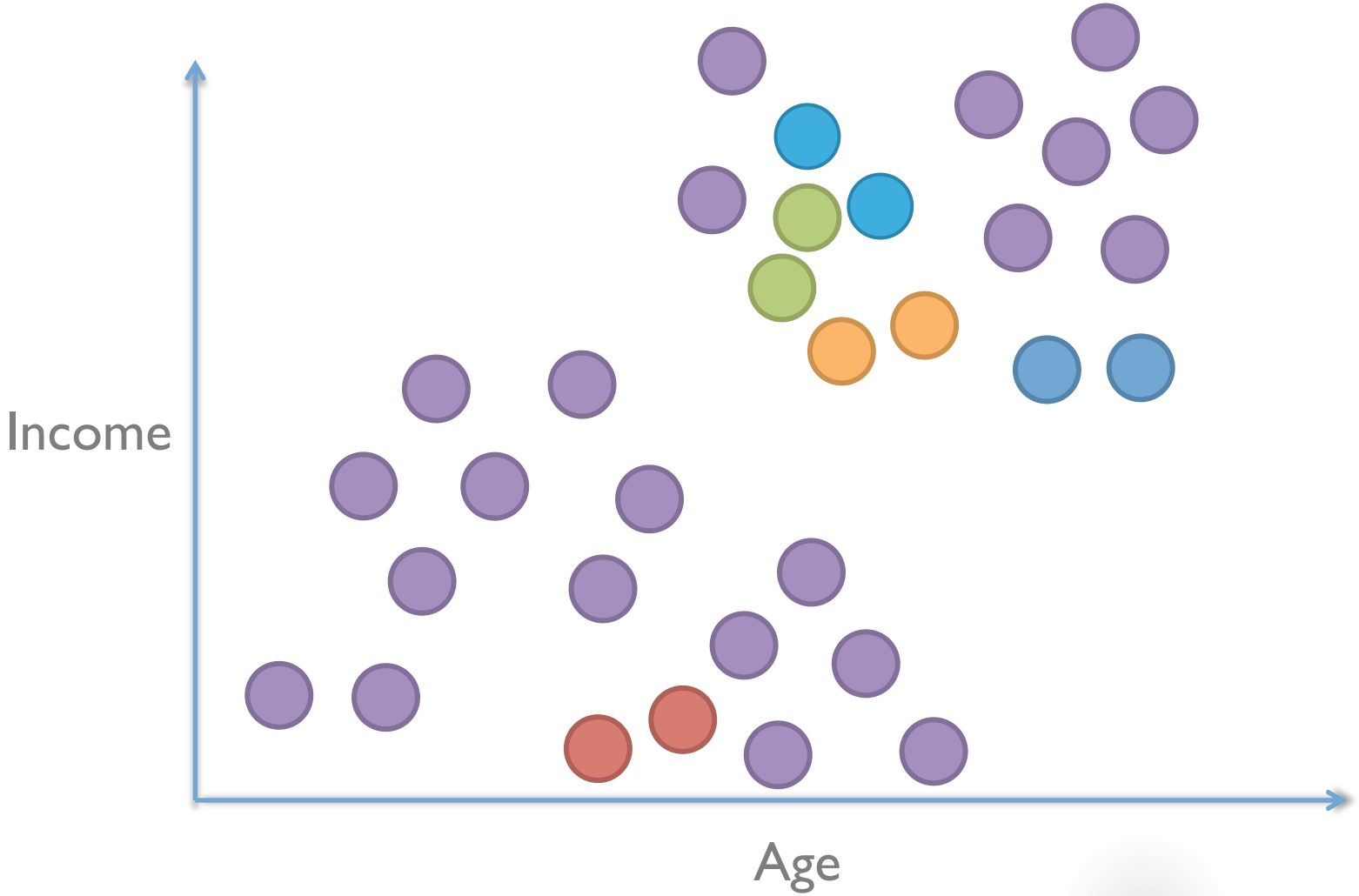
Agglomerative Hierarchical Clustering

Find next closet pair, merge



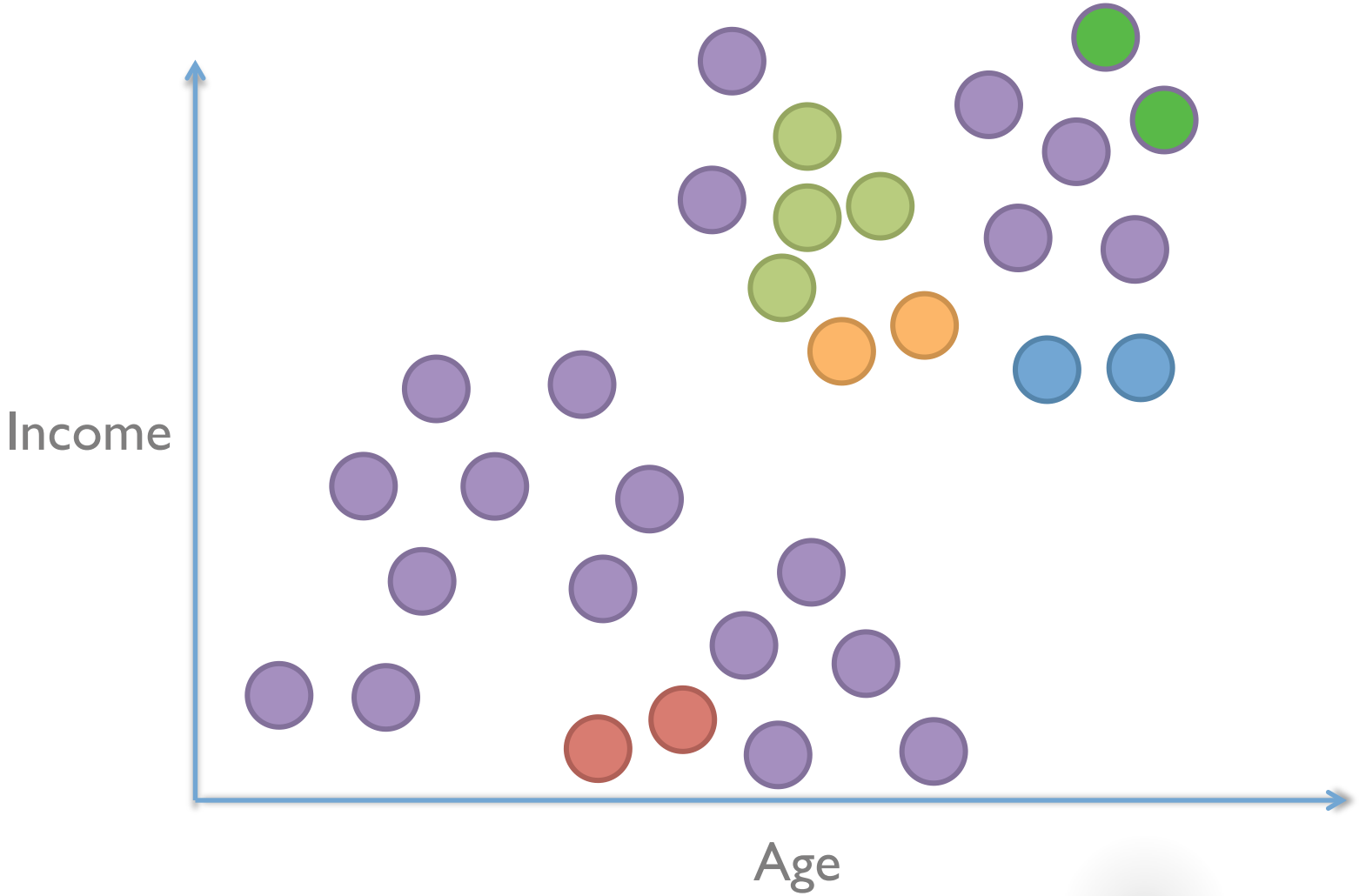
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



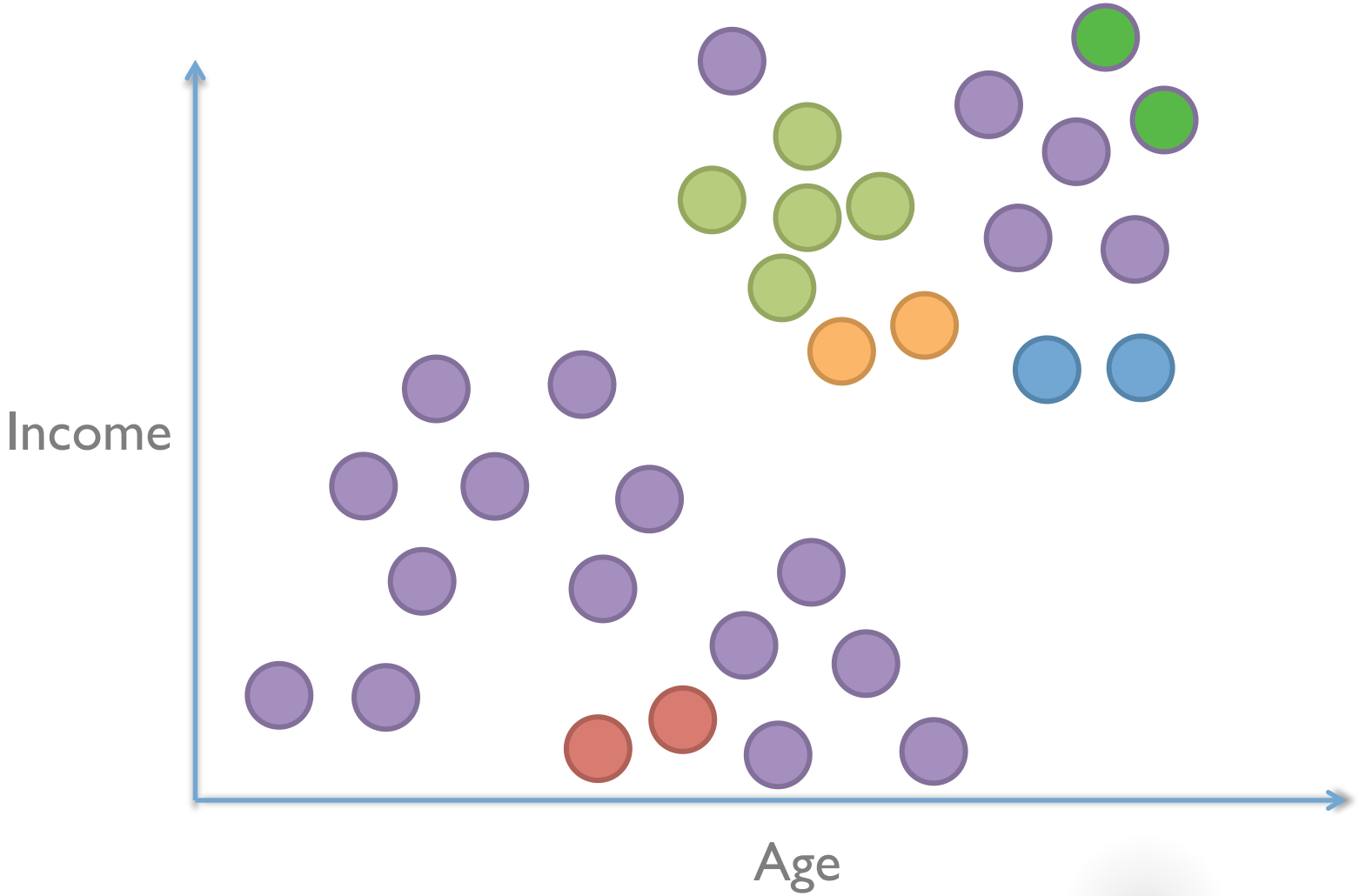
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



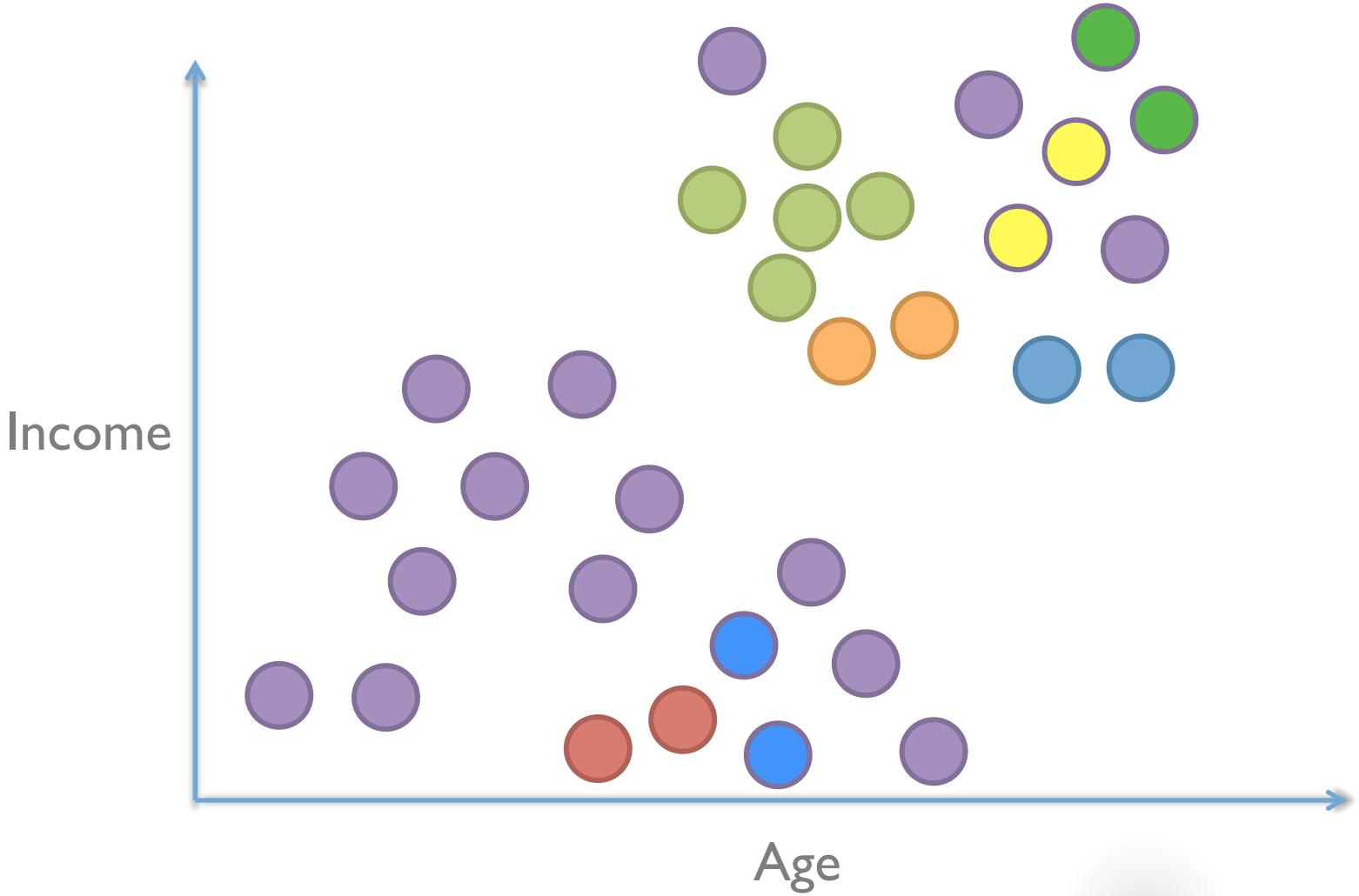
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



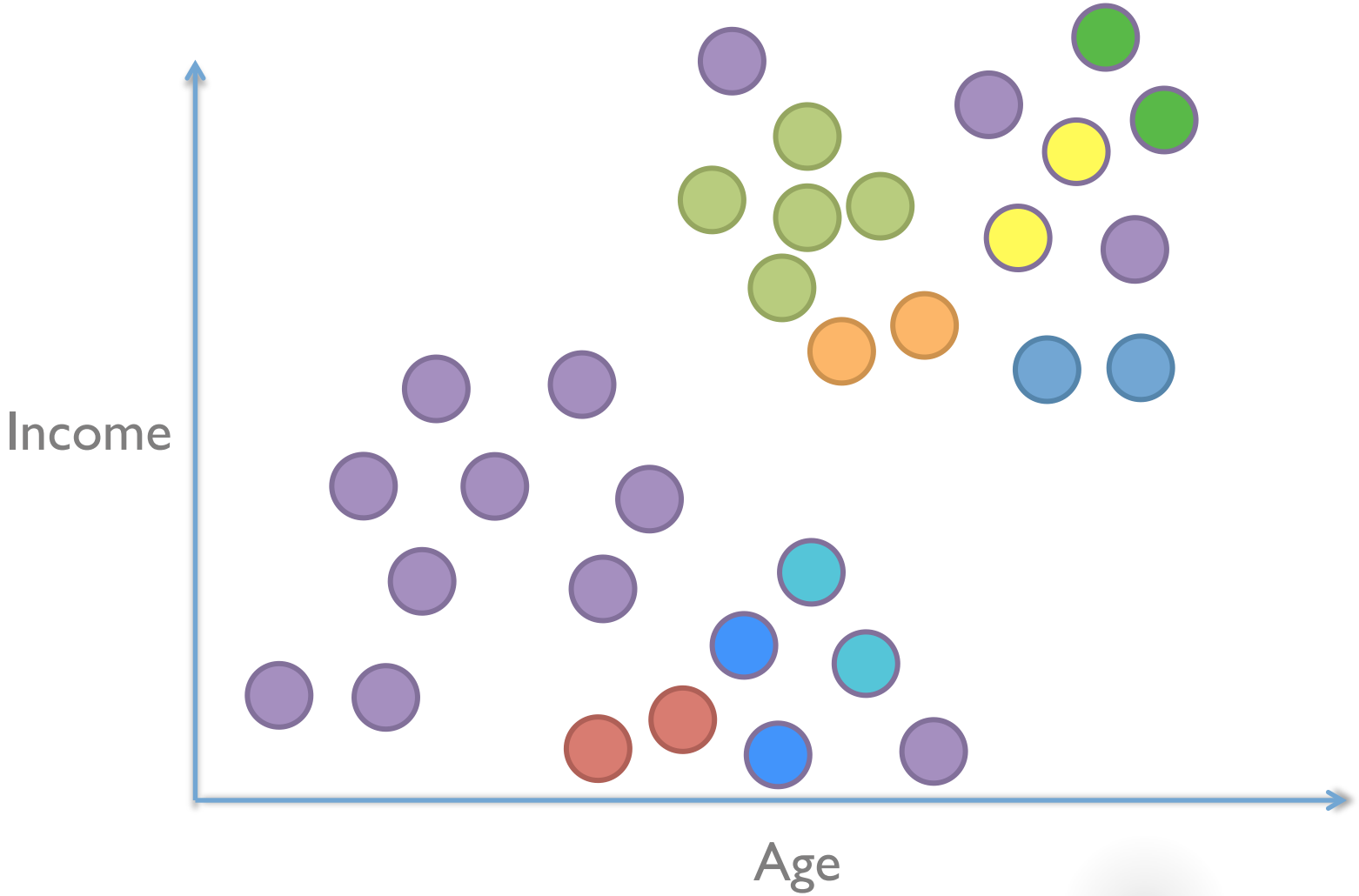
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



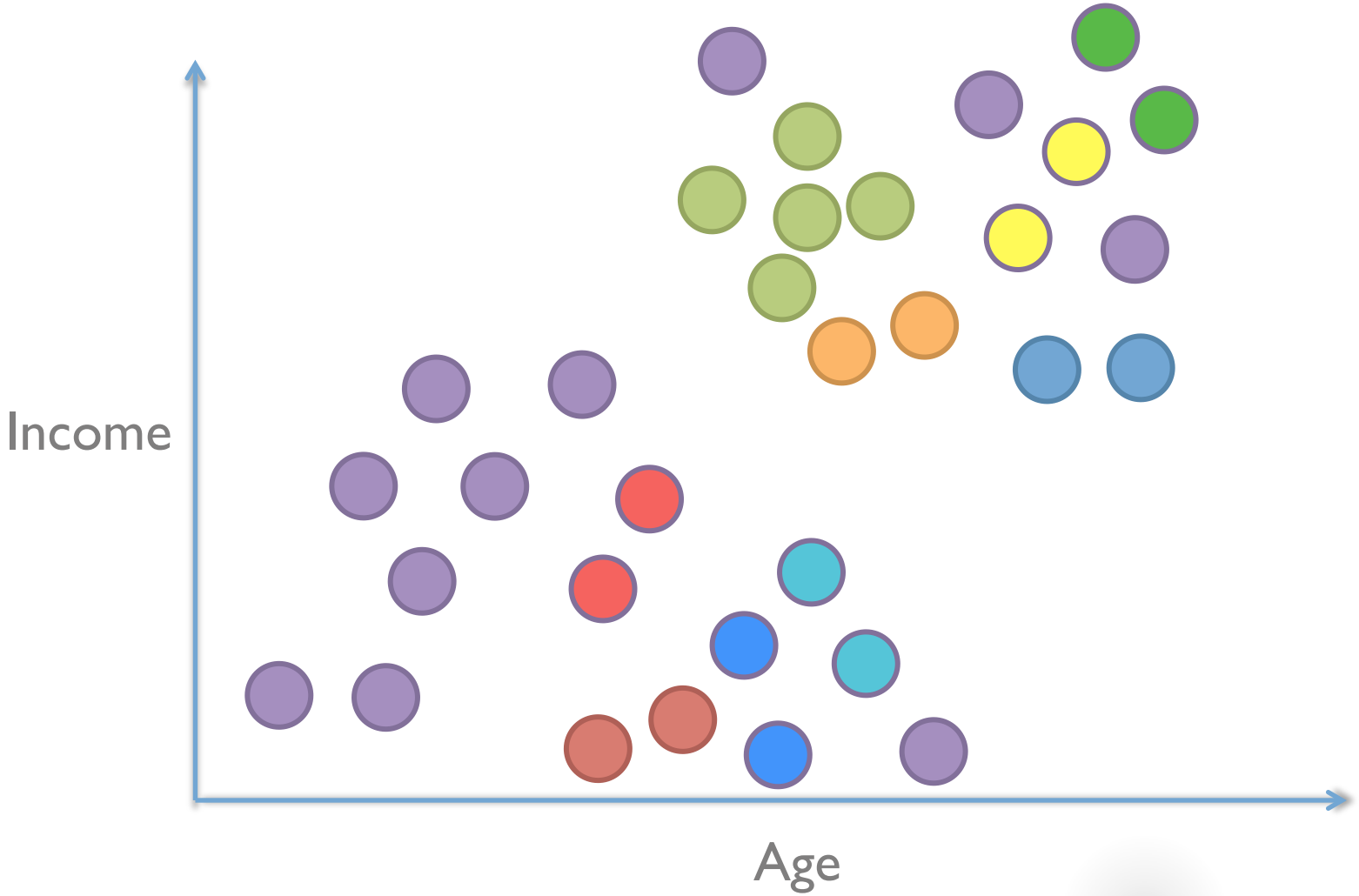
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



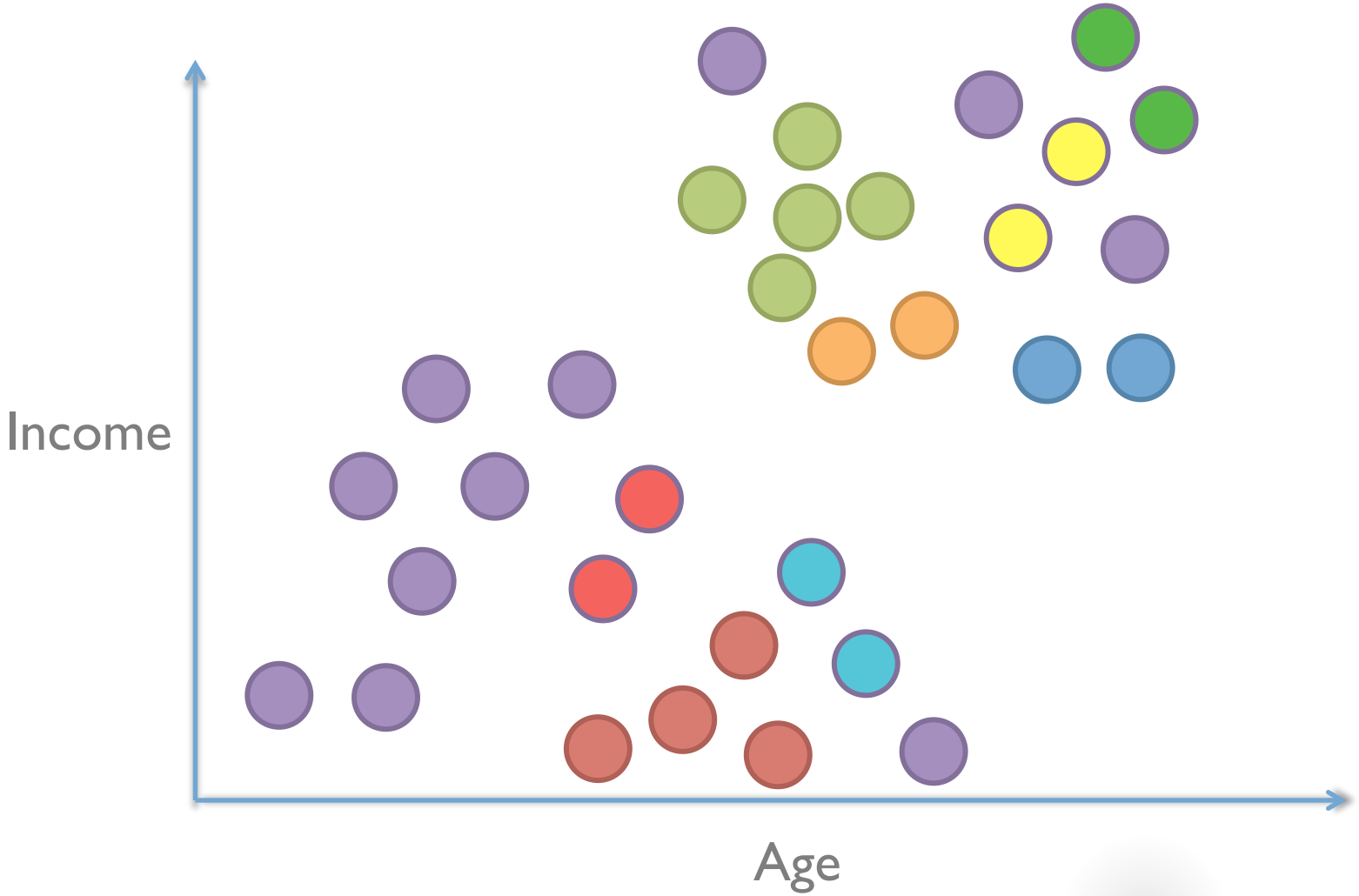
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



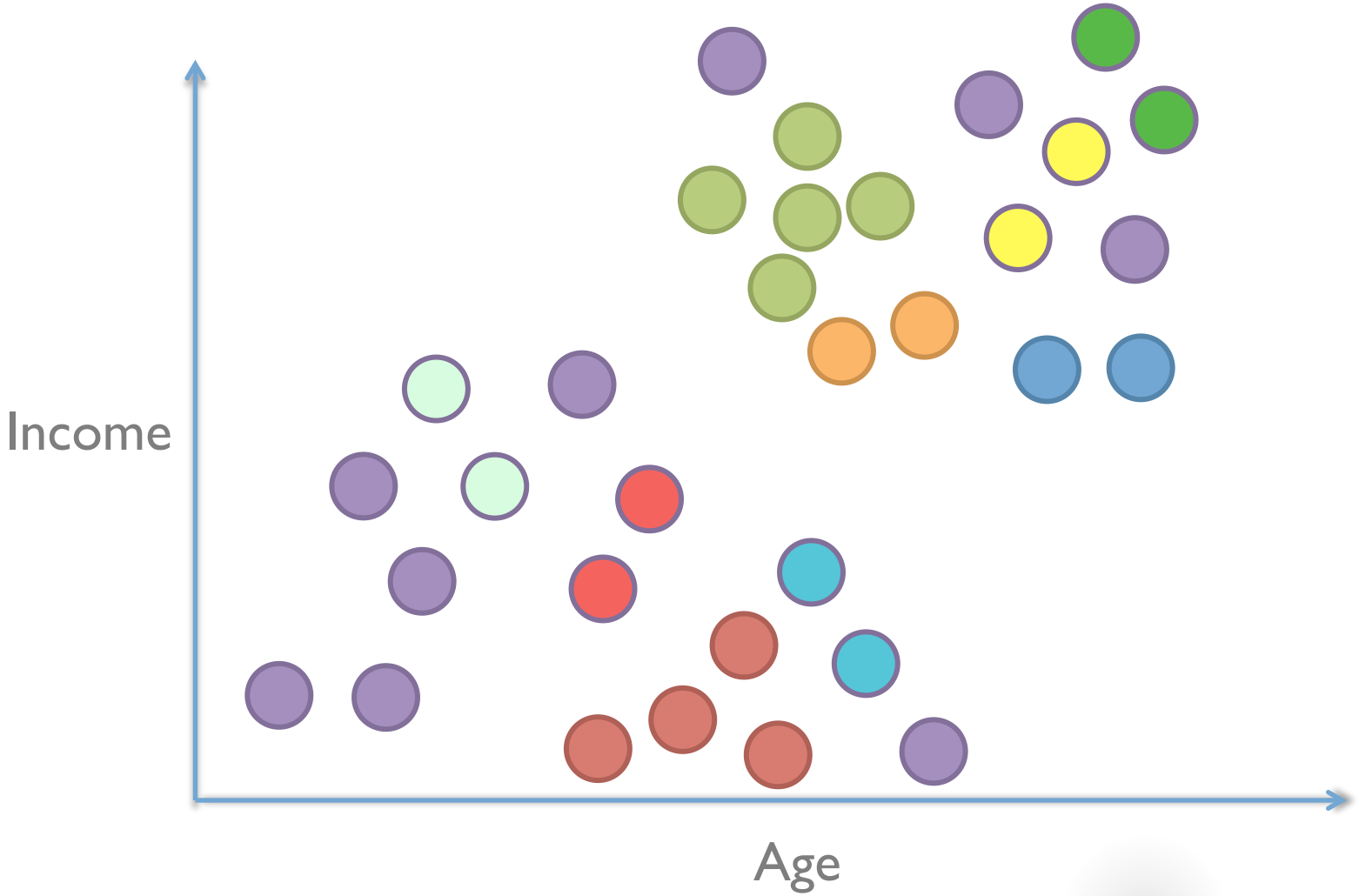
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



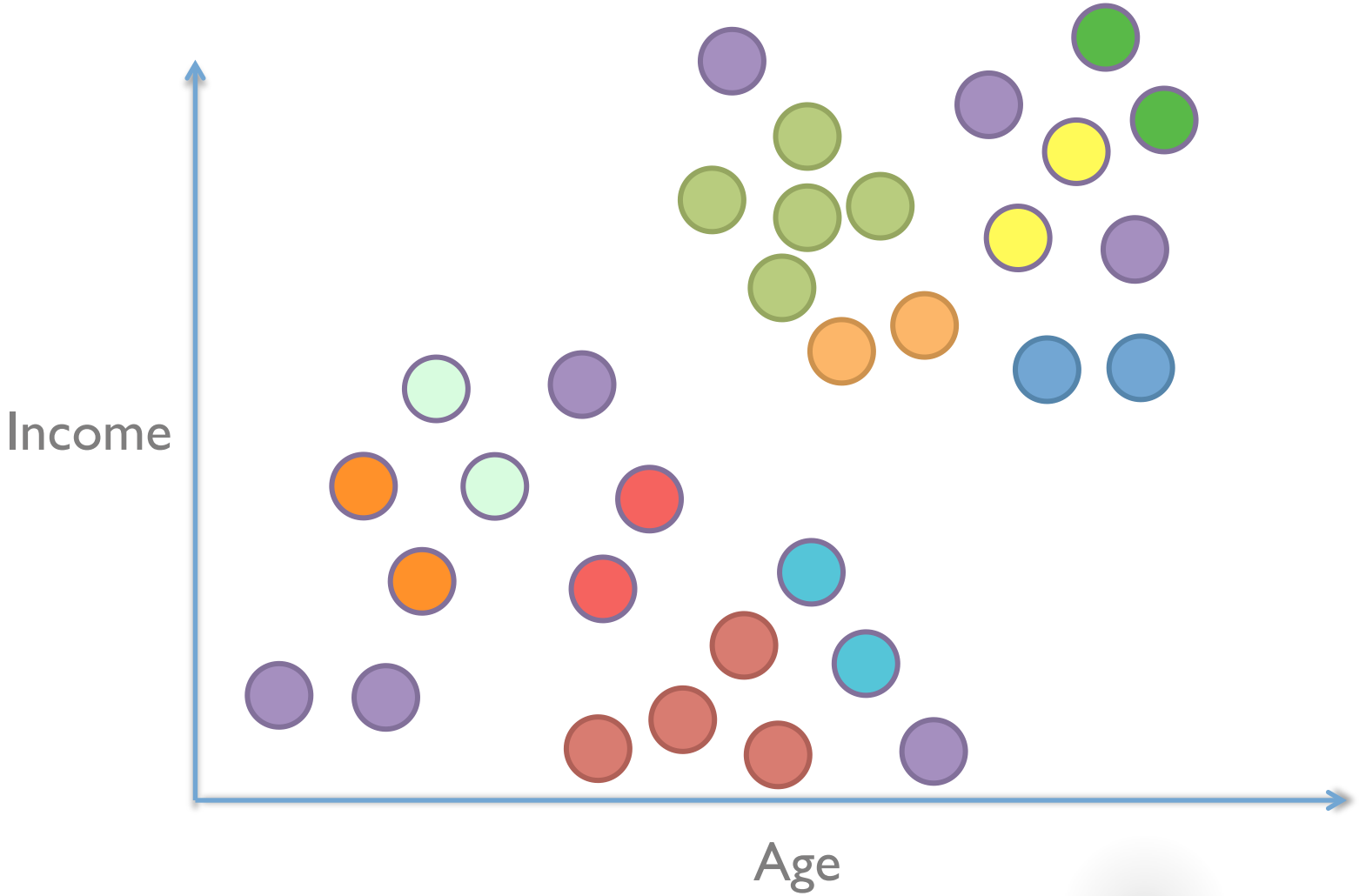
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



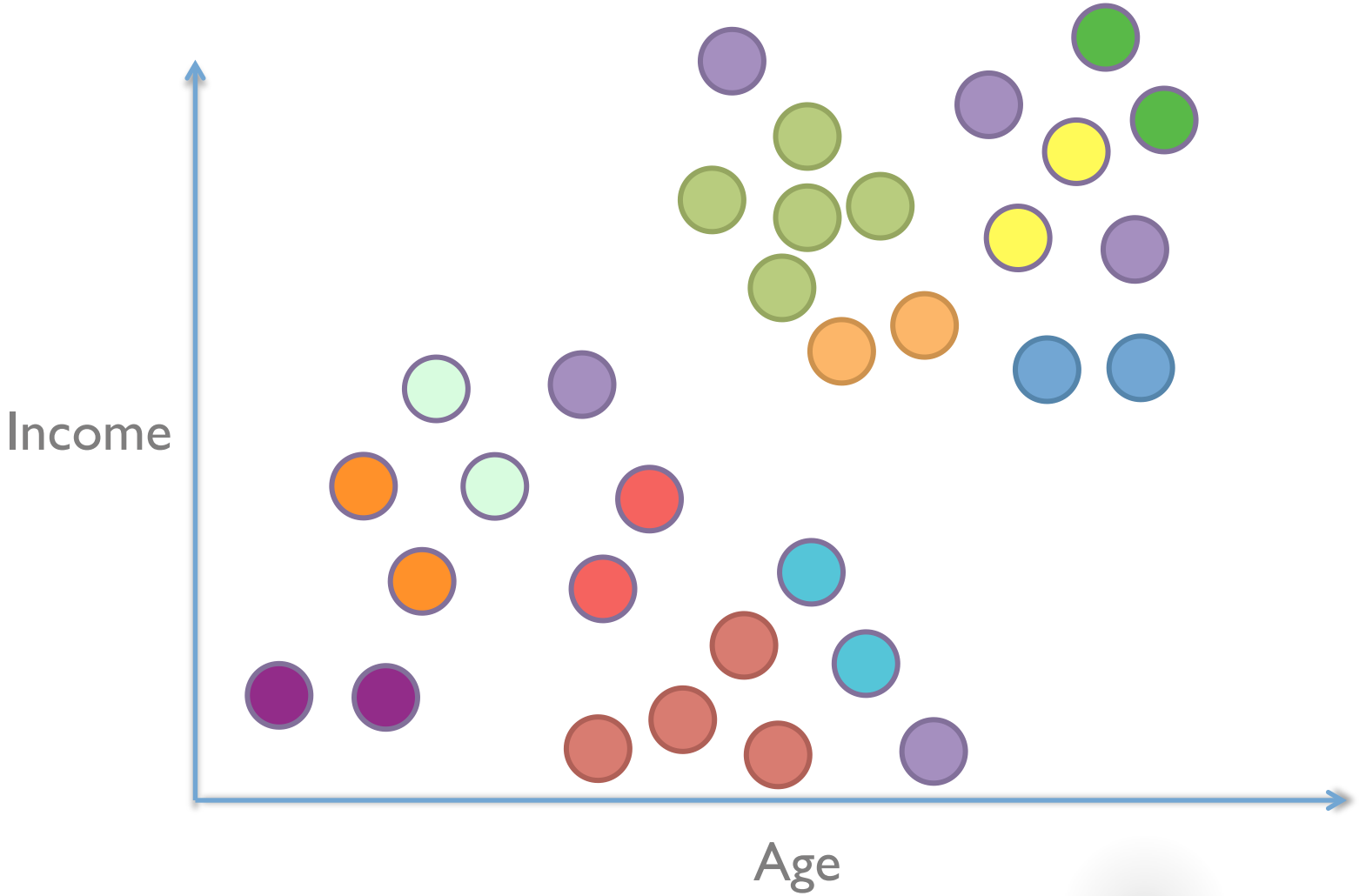
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



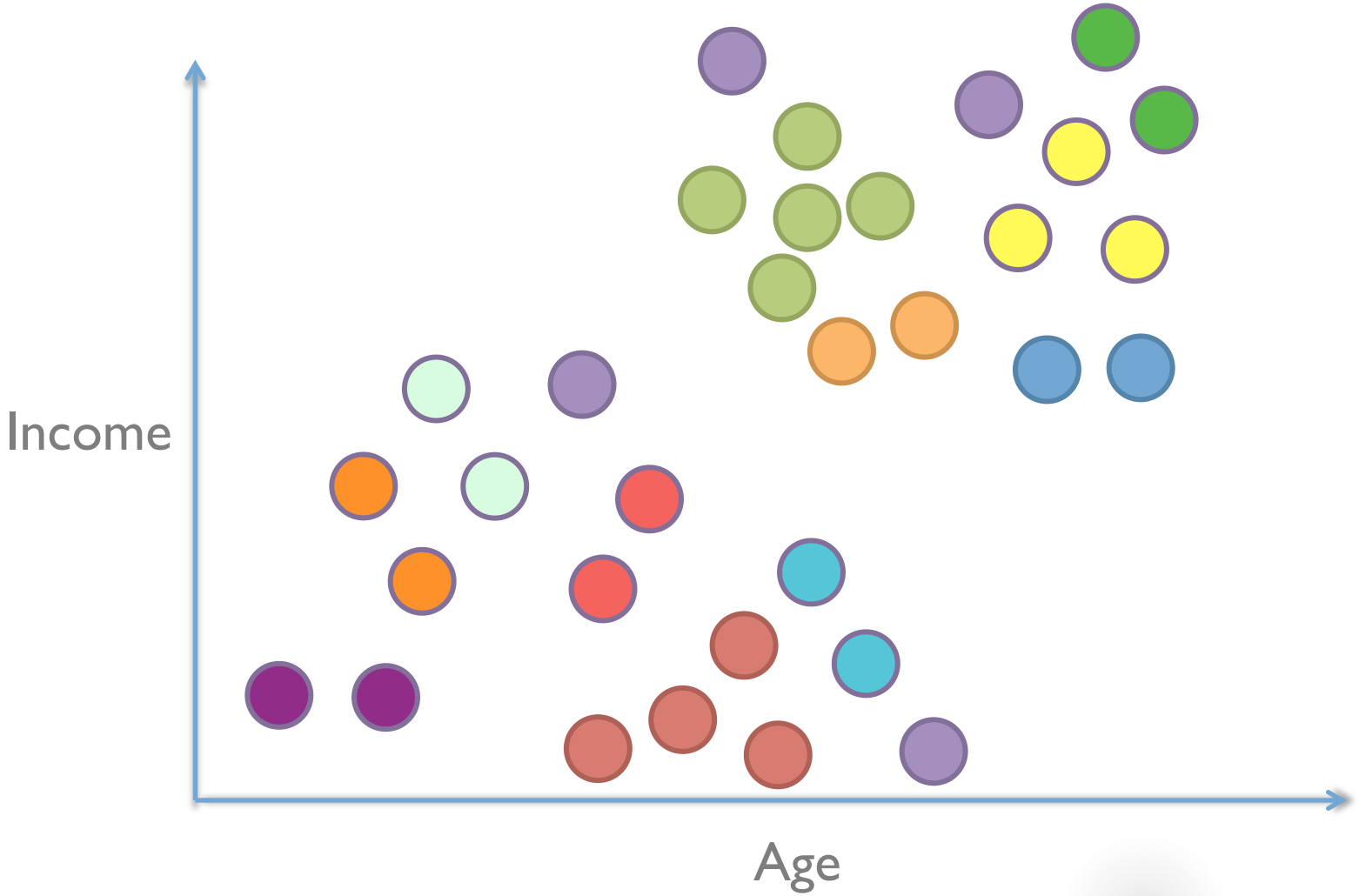
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



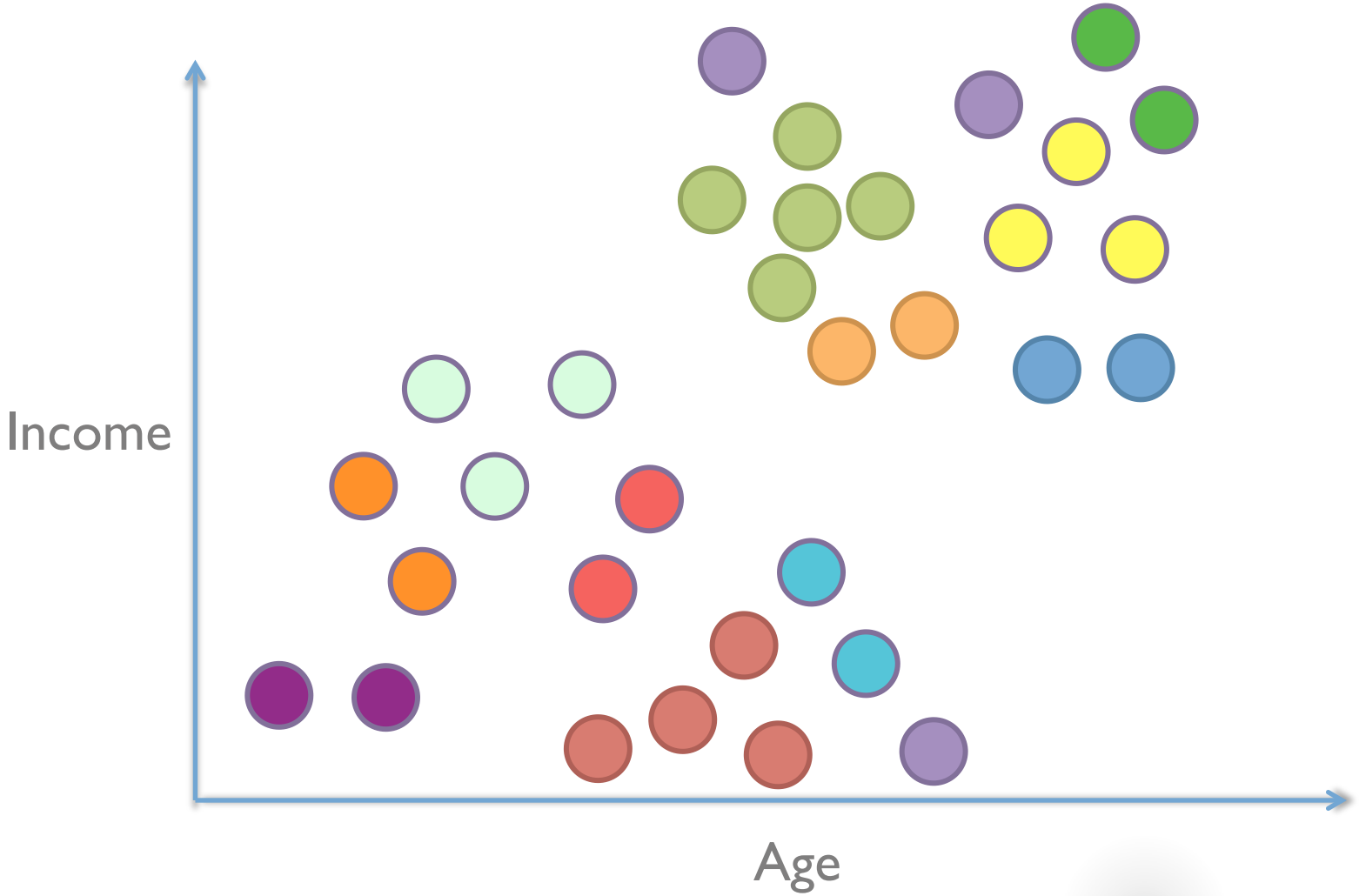
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



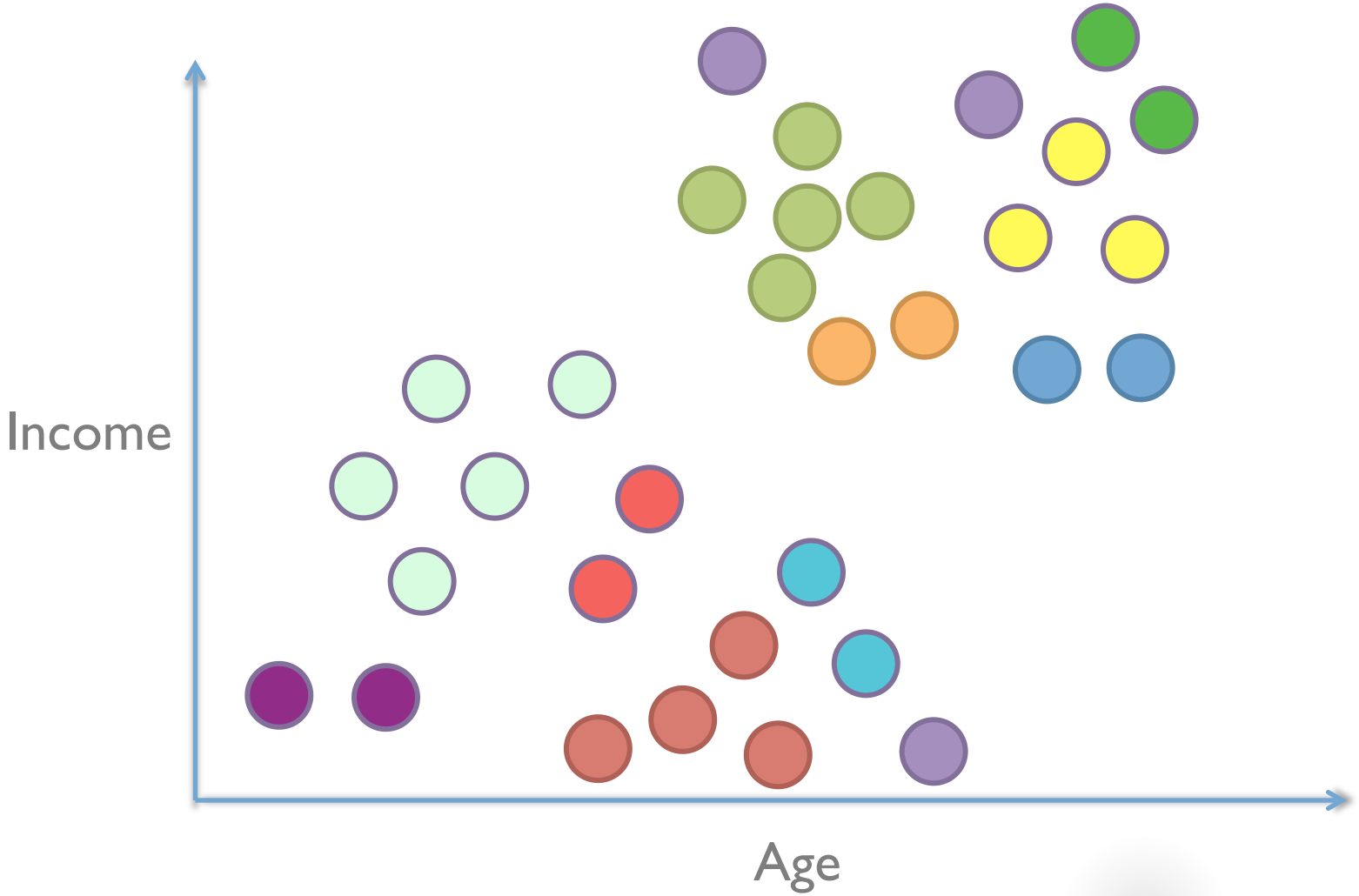
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



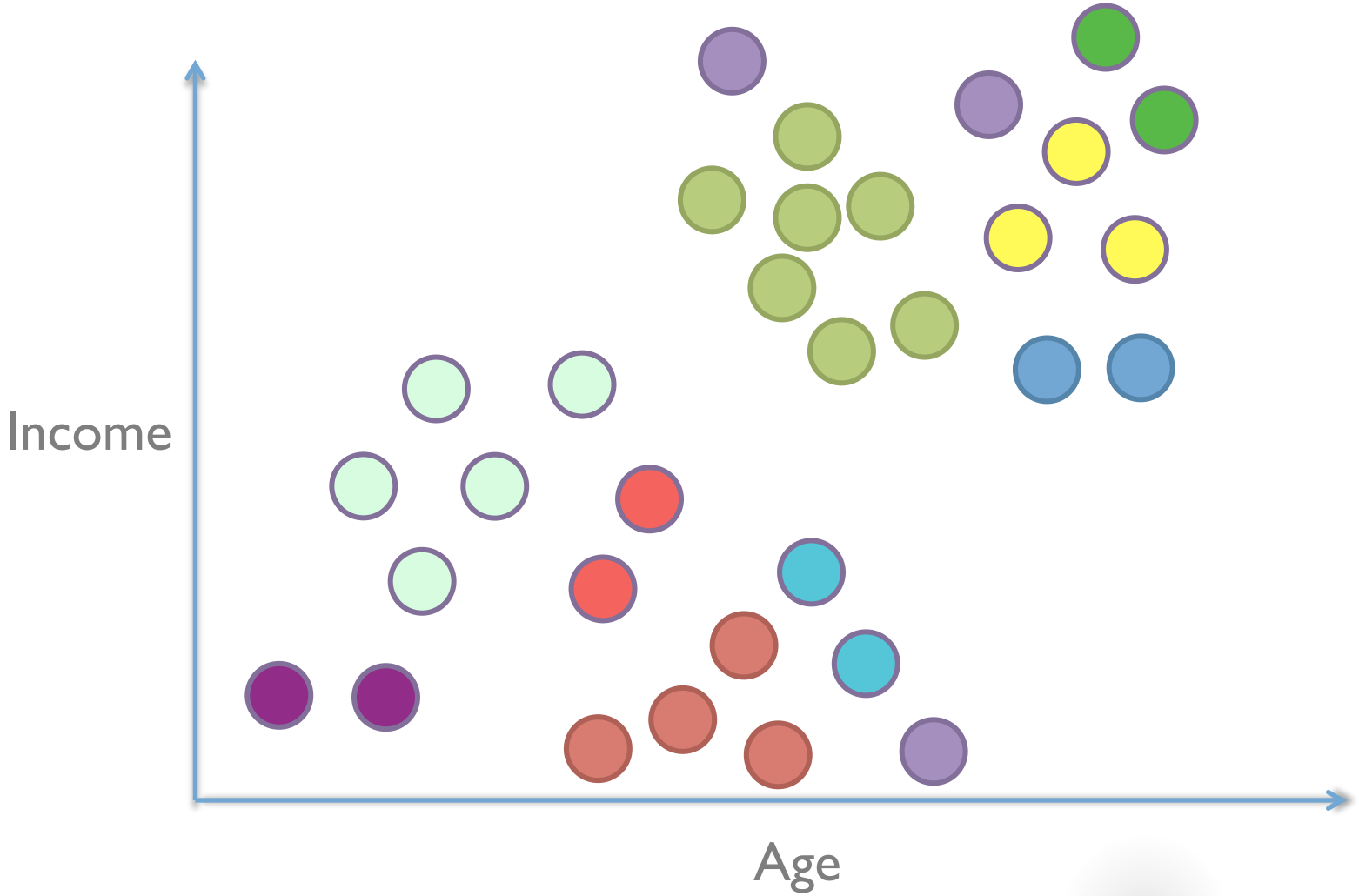
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



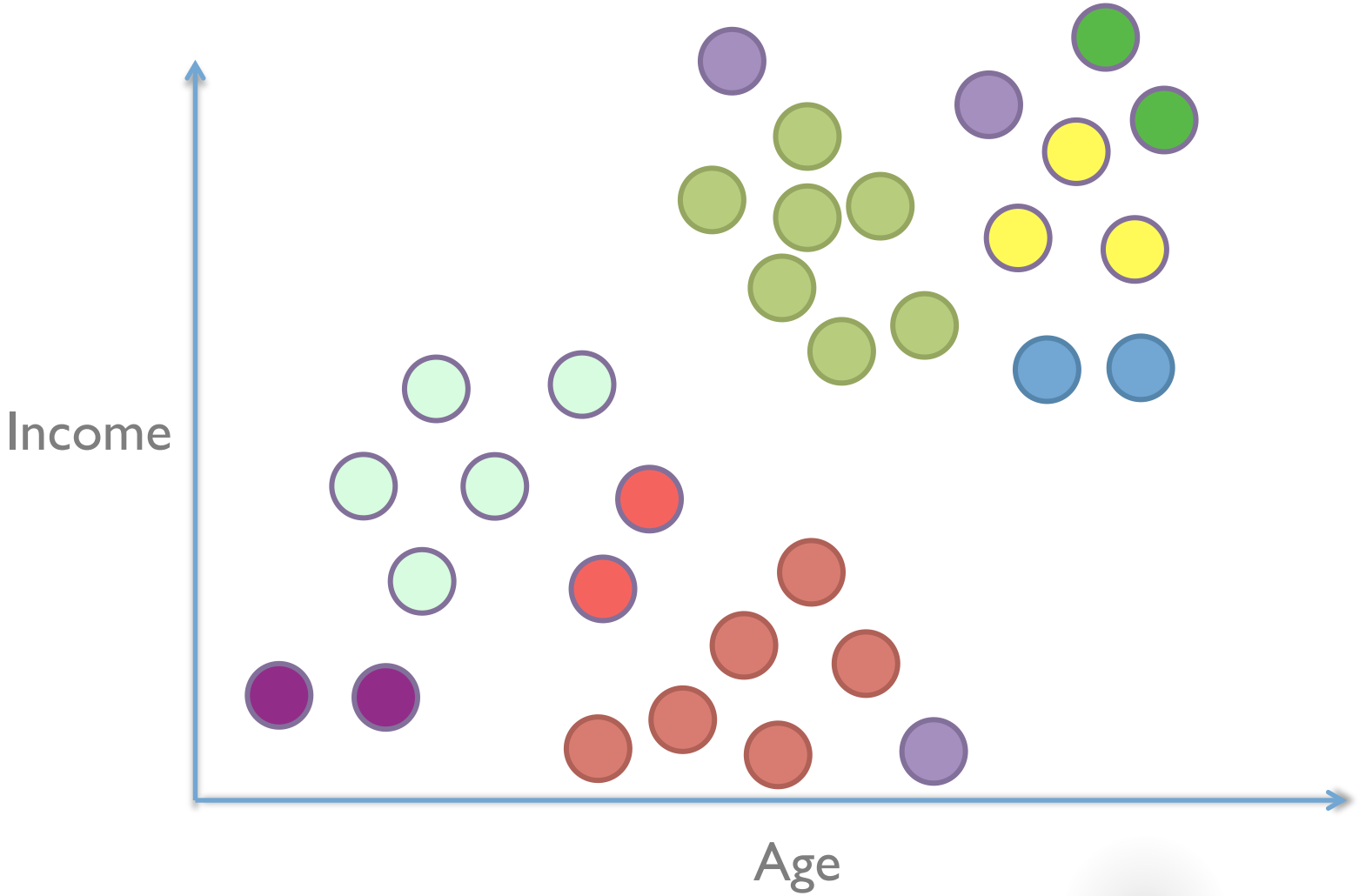
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



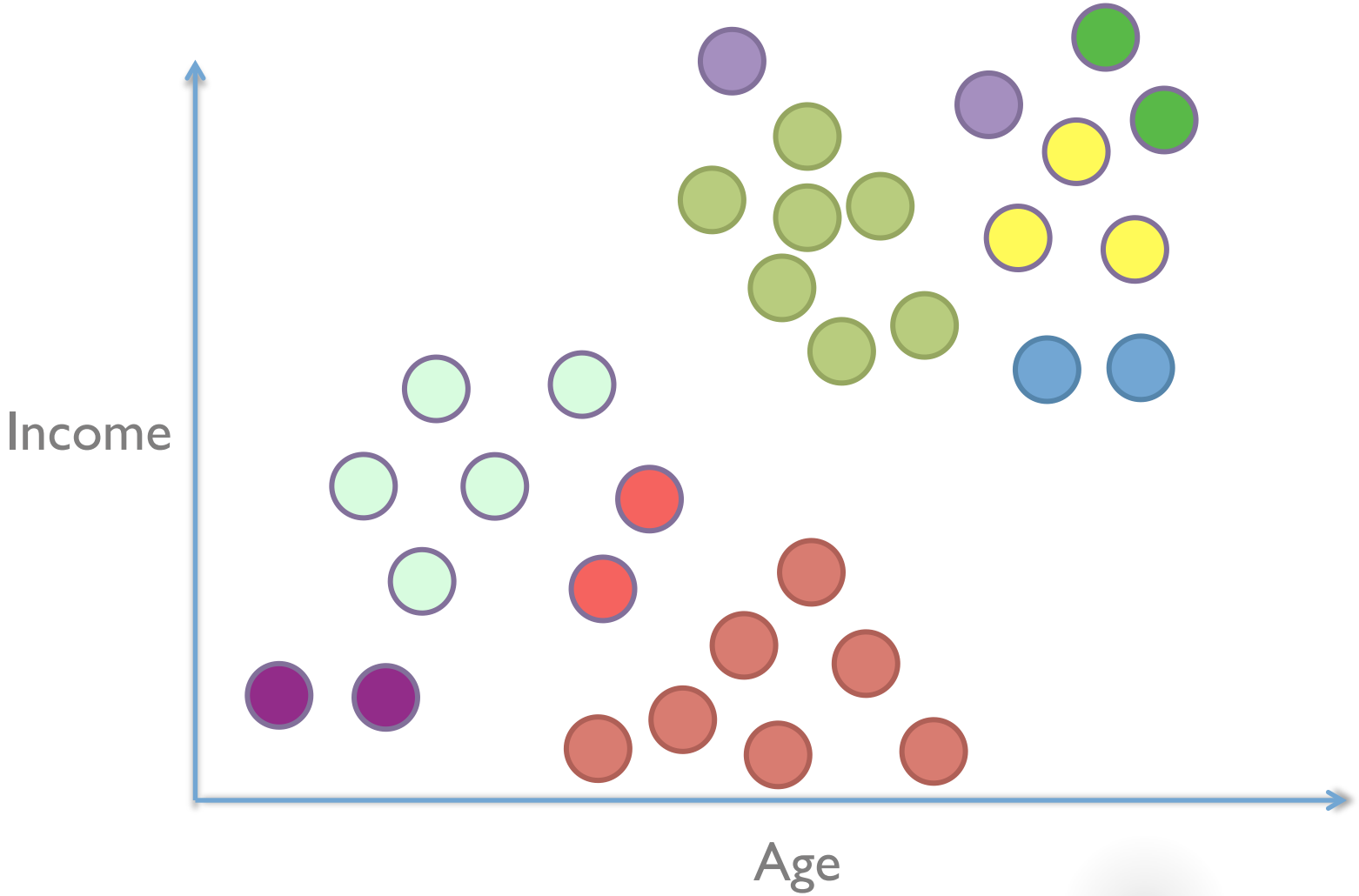
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



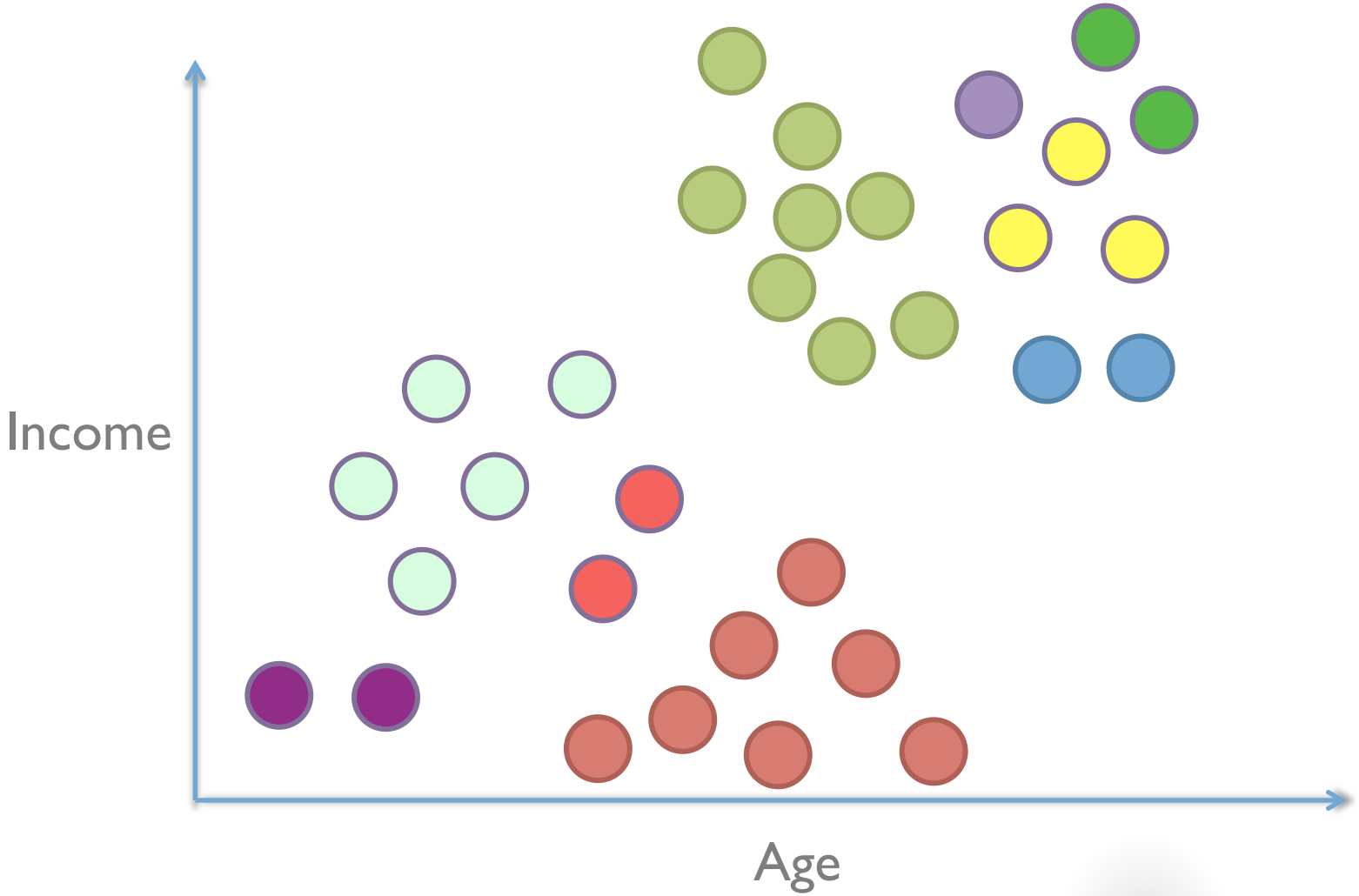
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



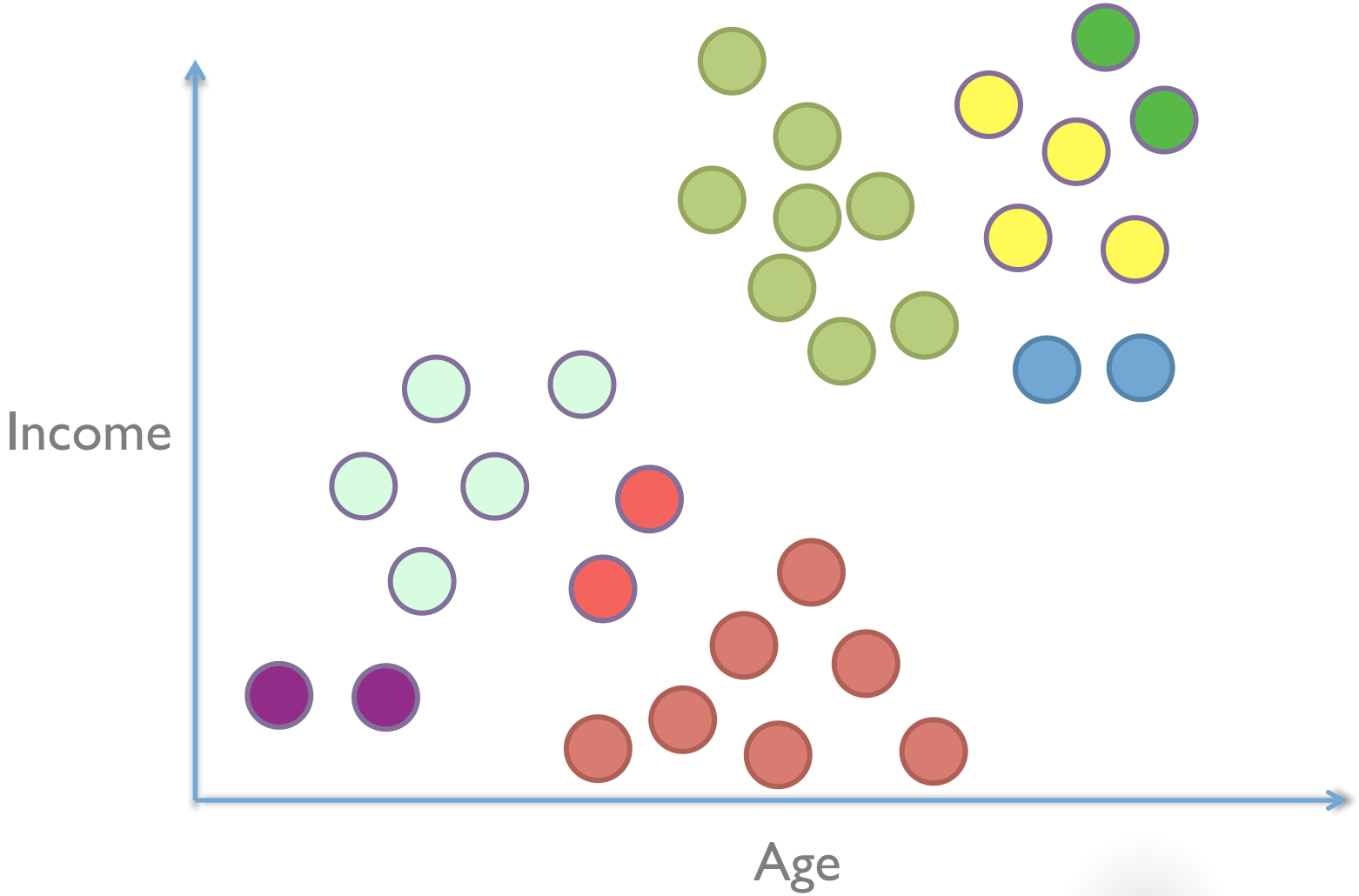
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



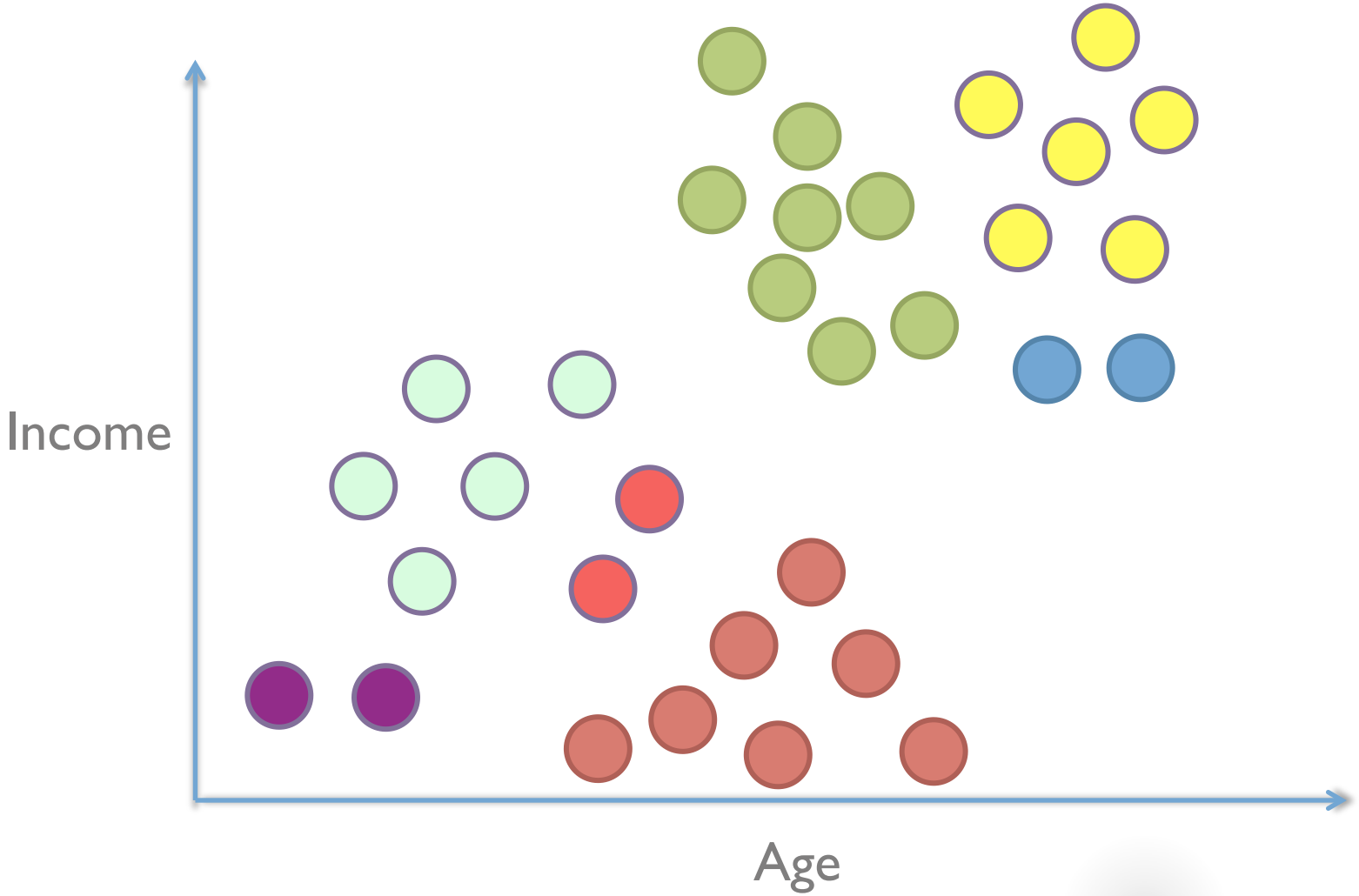
Agglomerative Hierarchical Clustering

If closest pair are clusters, same: merge



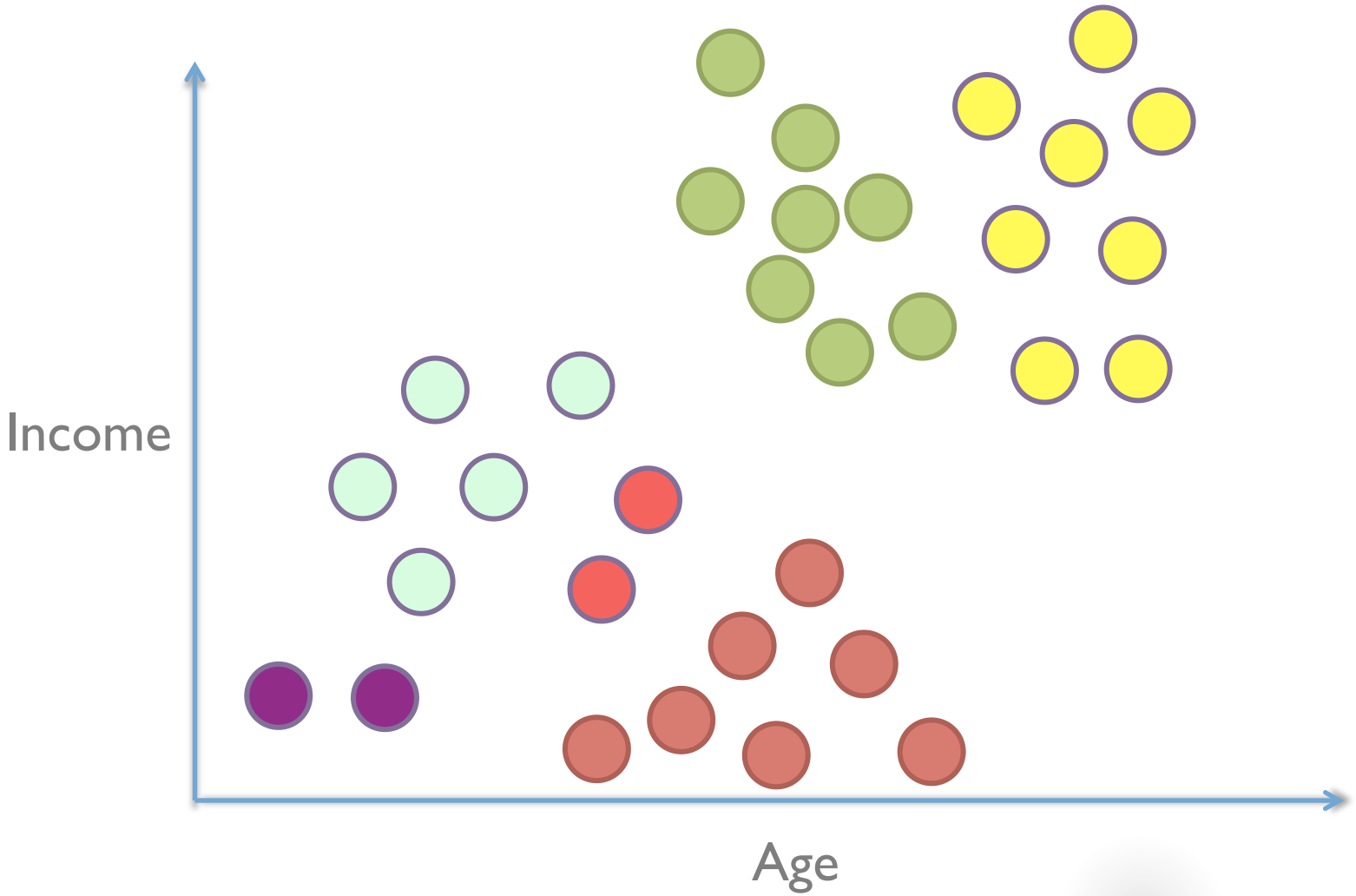
Agglomerative Hierarchical Clustering

Current num_clusters = 7



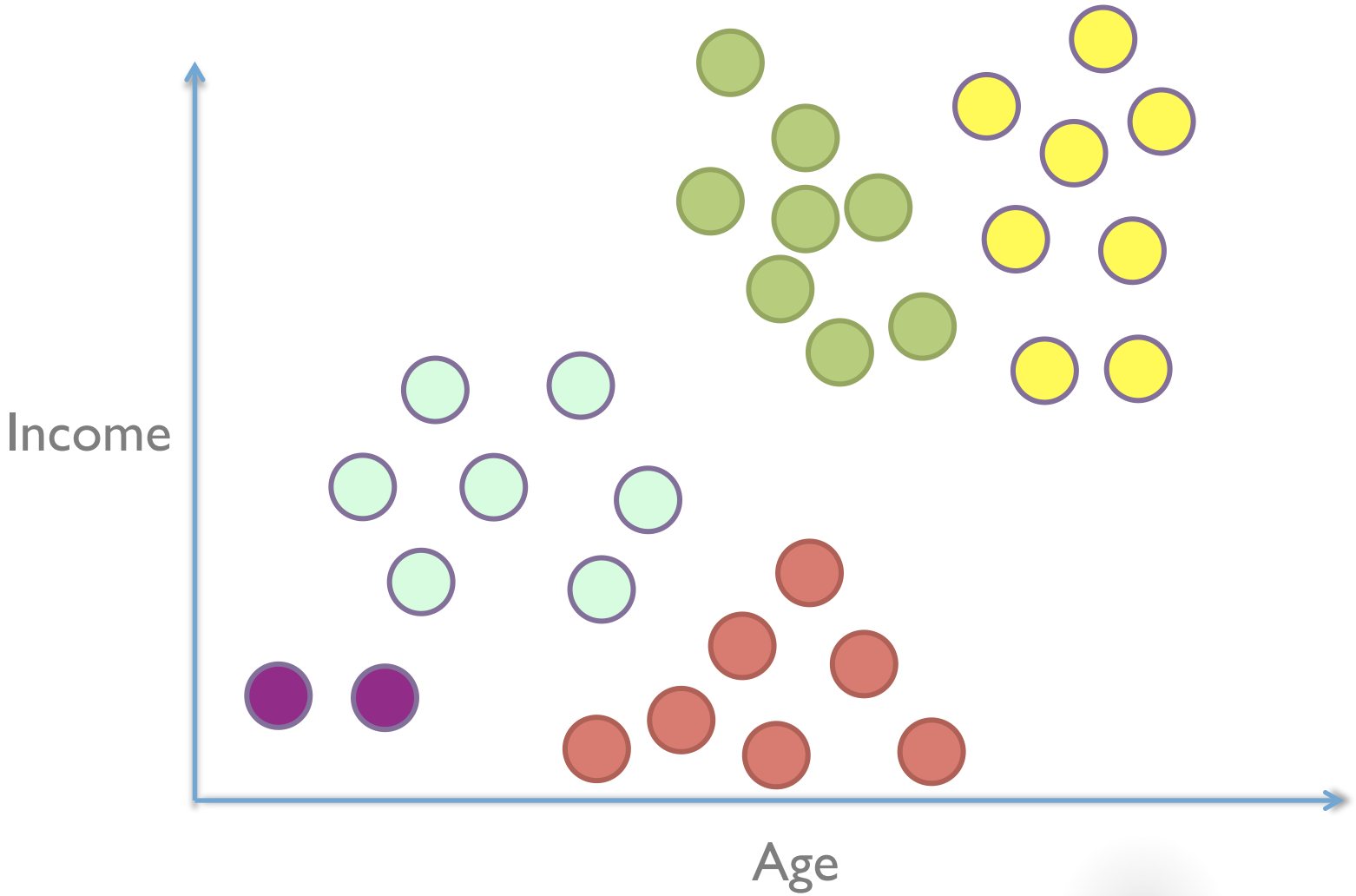
Agglomerative Hierarchical Clustering

Current num_clusters = 6



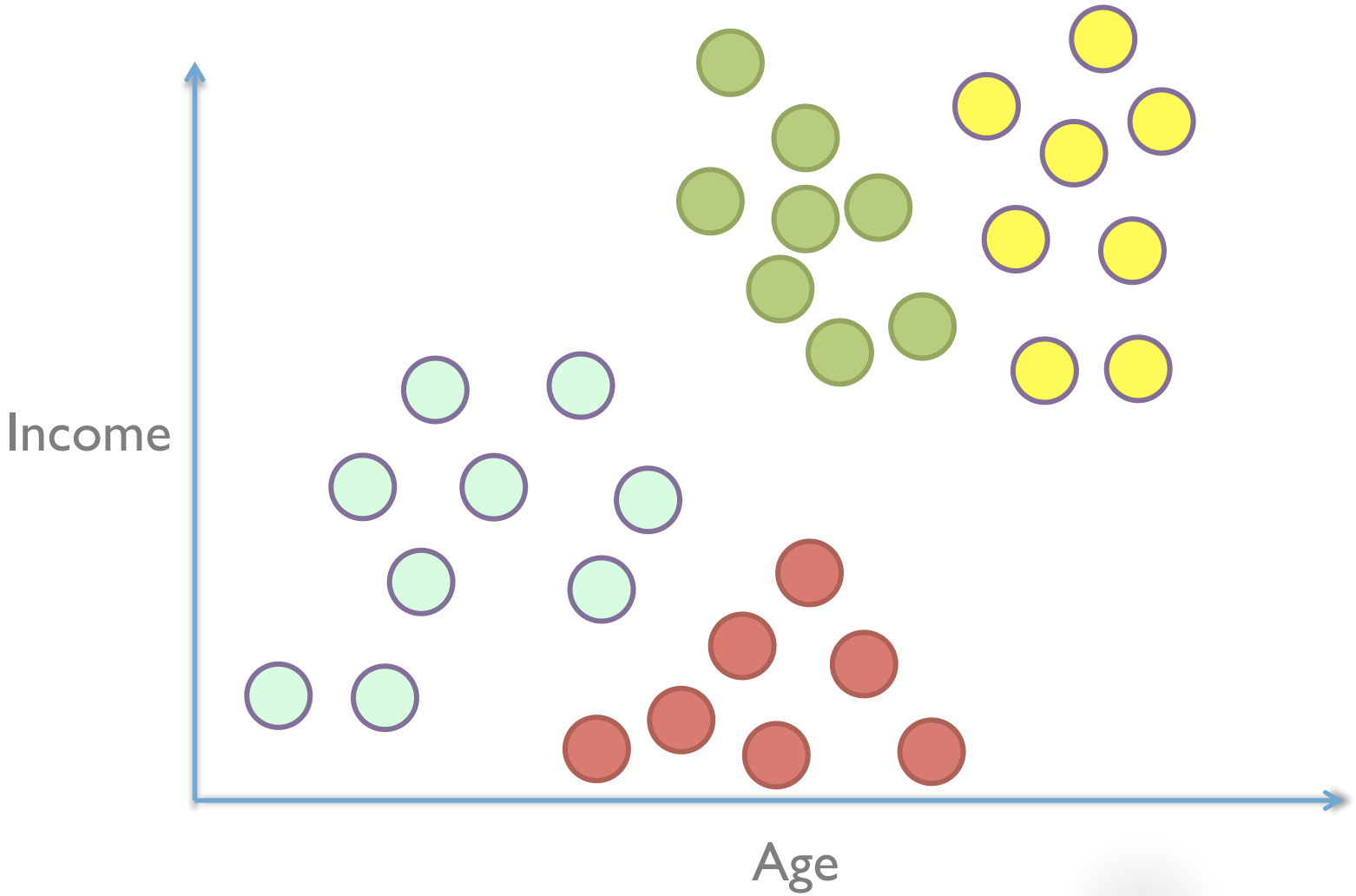
Agglomerative Hierarchical Clustering

Current num_clusters = 5



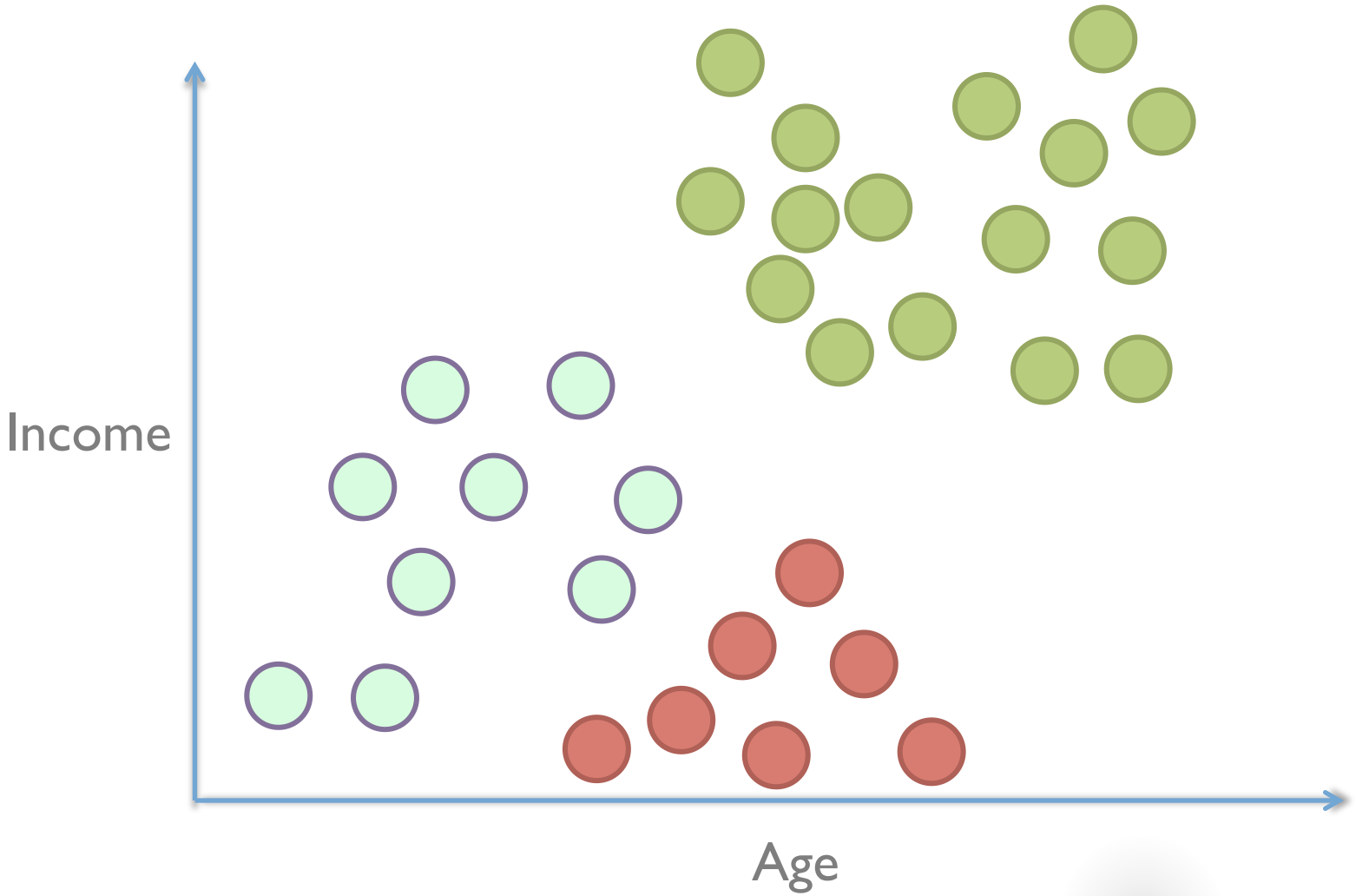
Agglomerative Hierarchical Clustering

Current num_clusters = 4



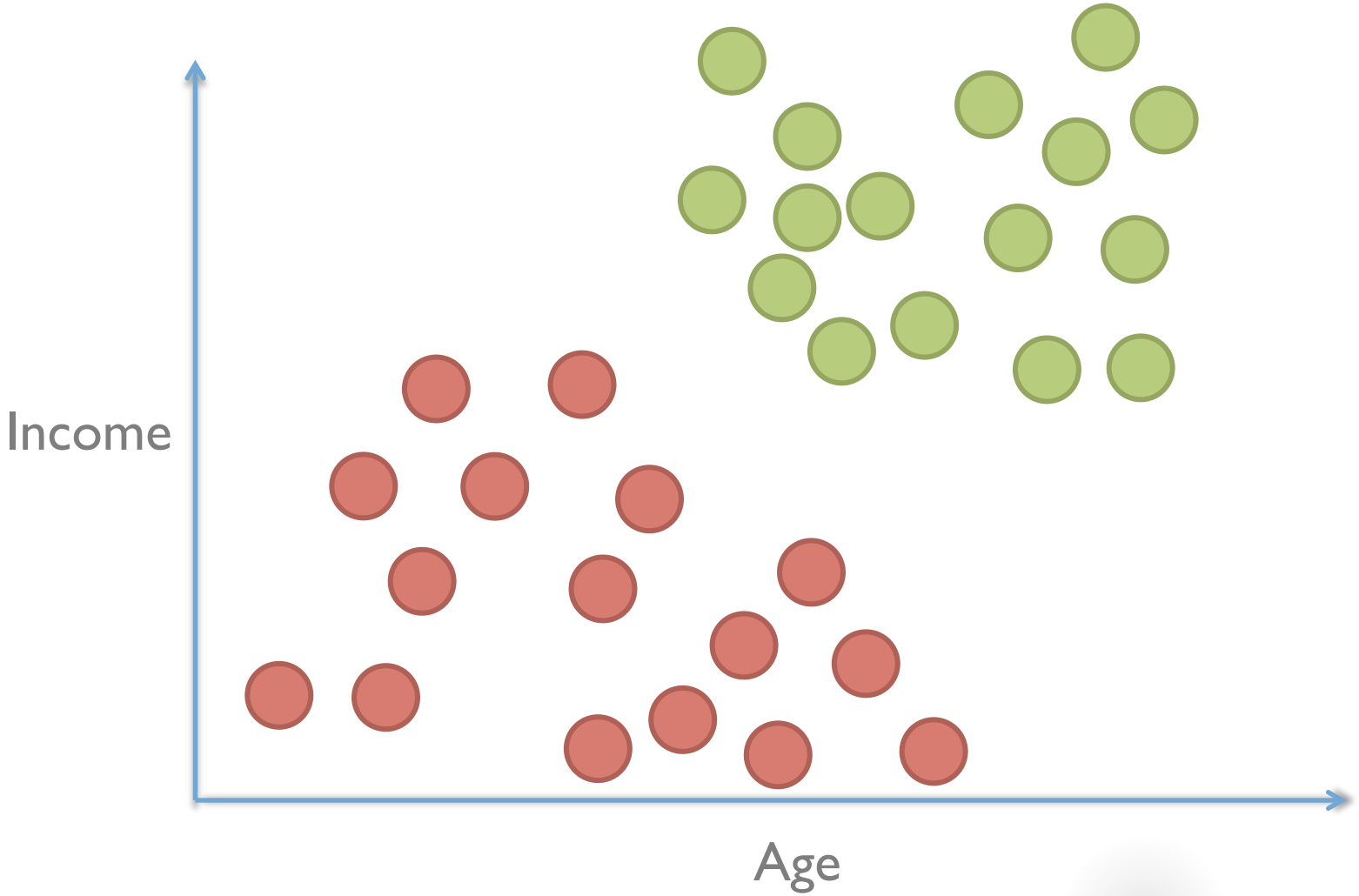
Agglomerative Hierarchical Clustering

Current num_clusters = 3



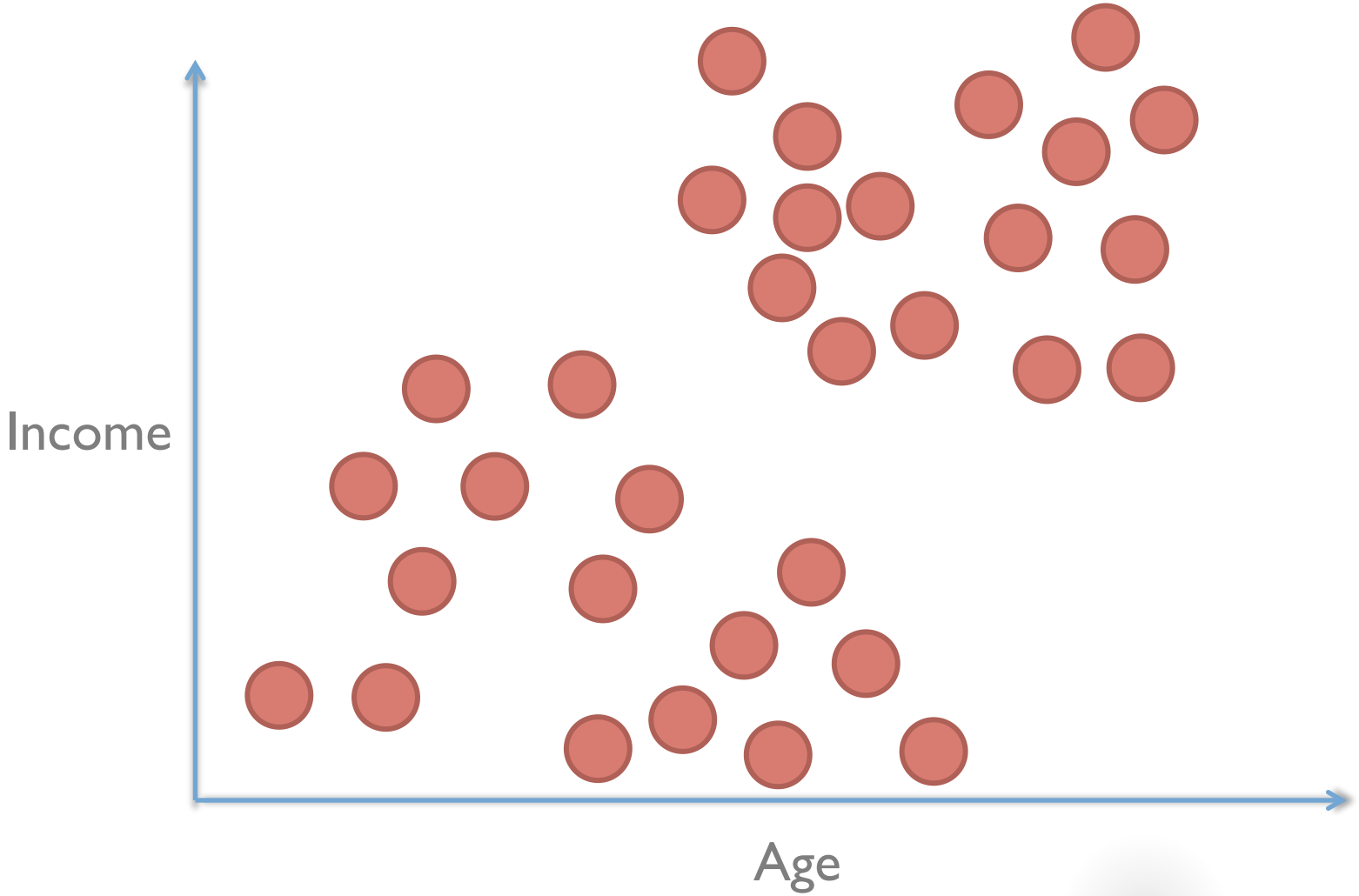
Agglomerative Hierarchical Clustering

Current num_clusters = 2



Agglomerative Hierarchical Clustering

Current num_clusters = 1



Agglomerative Hierarchical Clustering

Stop either

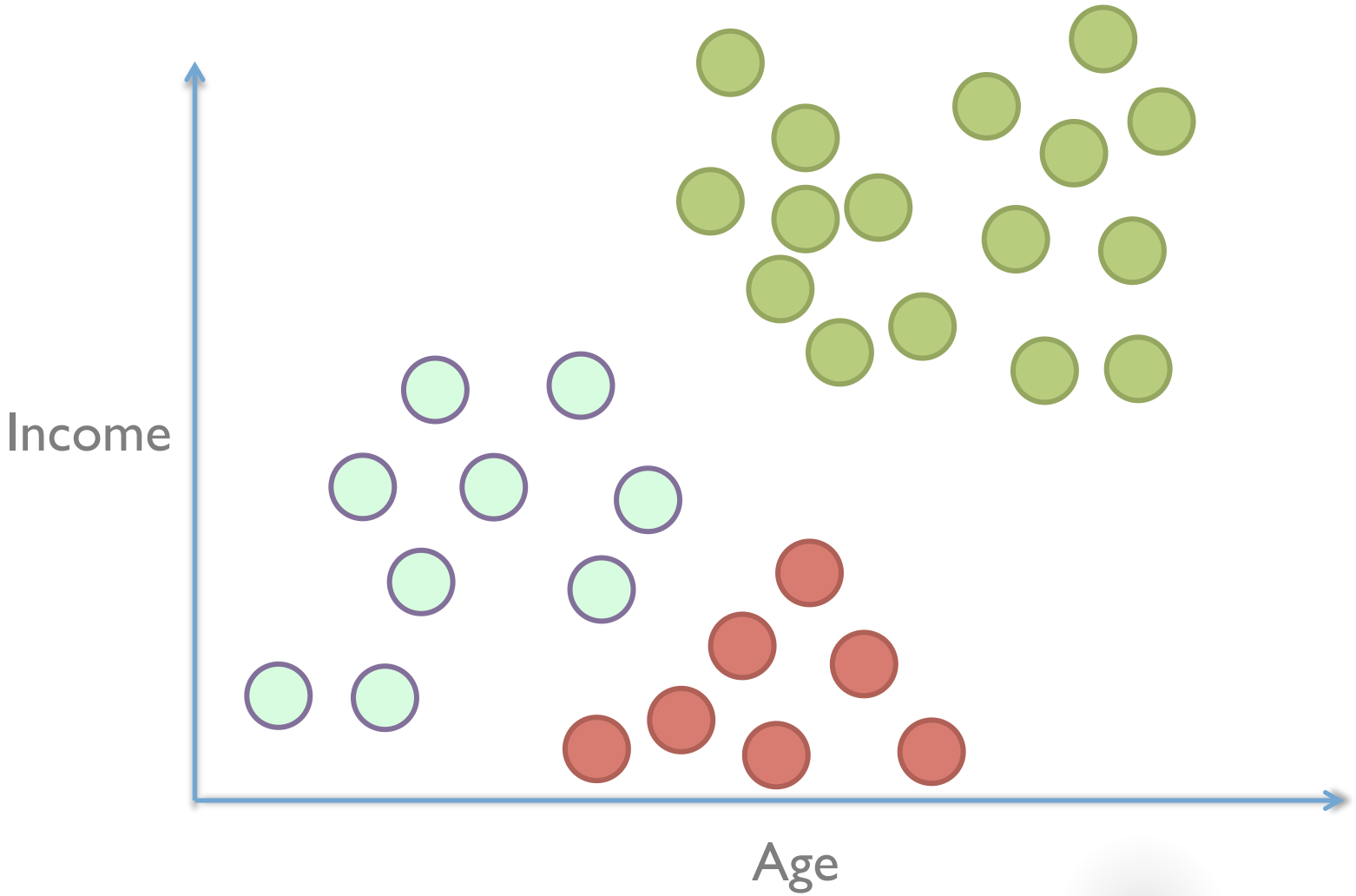
- when you reach the correct num_clusters (next step would mean fewer clusters than desired)

Or

- when min cluster distance reaches a set value (next step would mean merging along too large a distance)

Agglomerative Hierarchical Clustering

Current num_clusters = 3

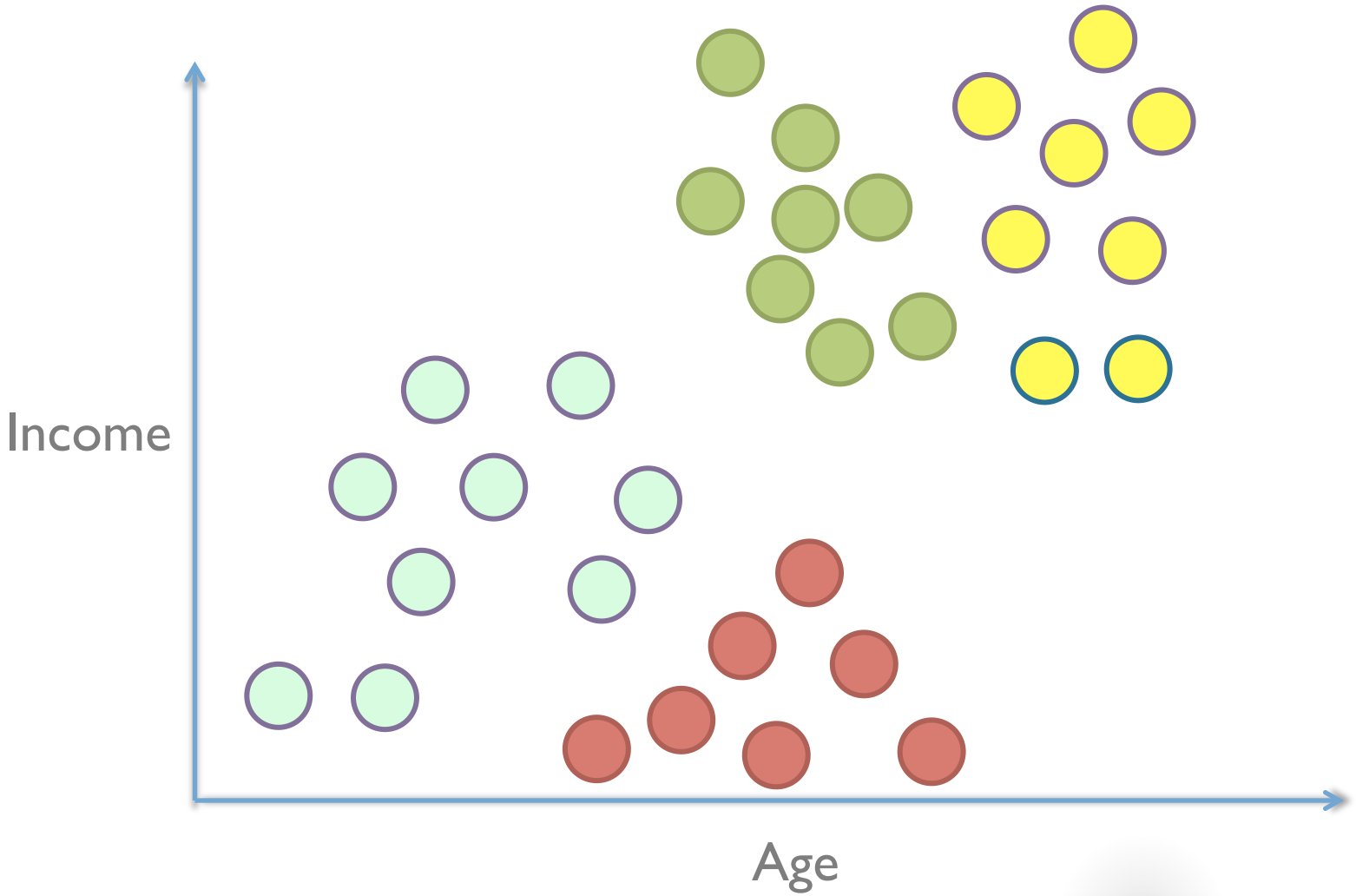


Agglomerative Hierarchical Clustering

Current num_clusters = 3

Agglomerative Hierarchical Clustering

Current num_clusters = 4

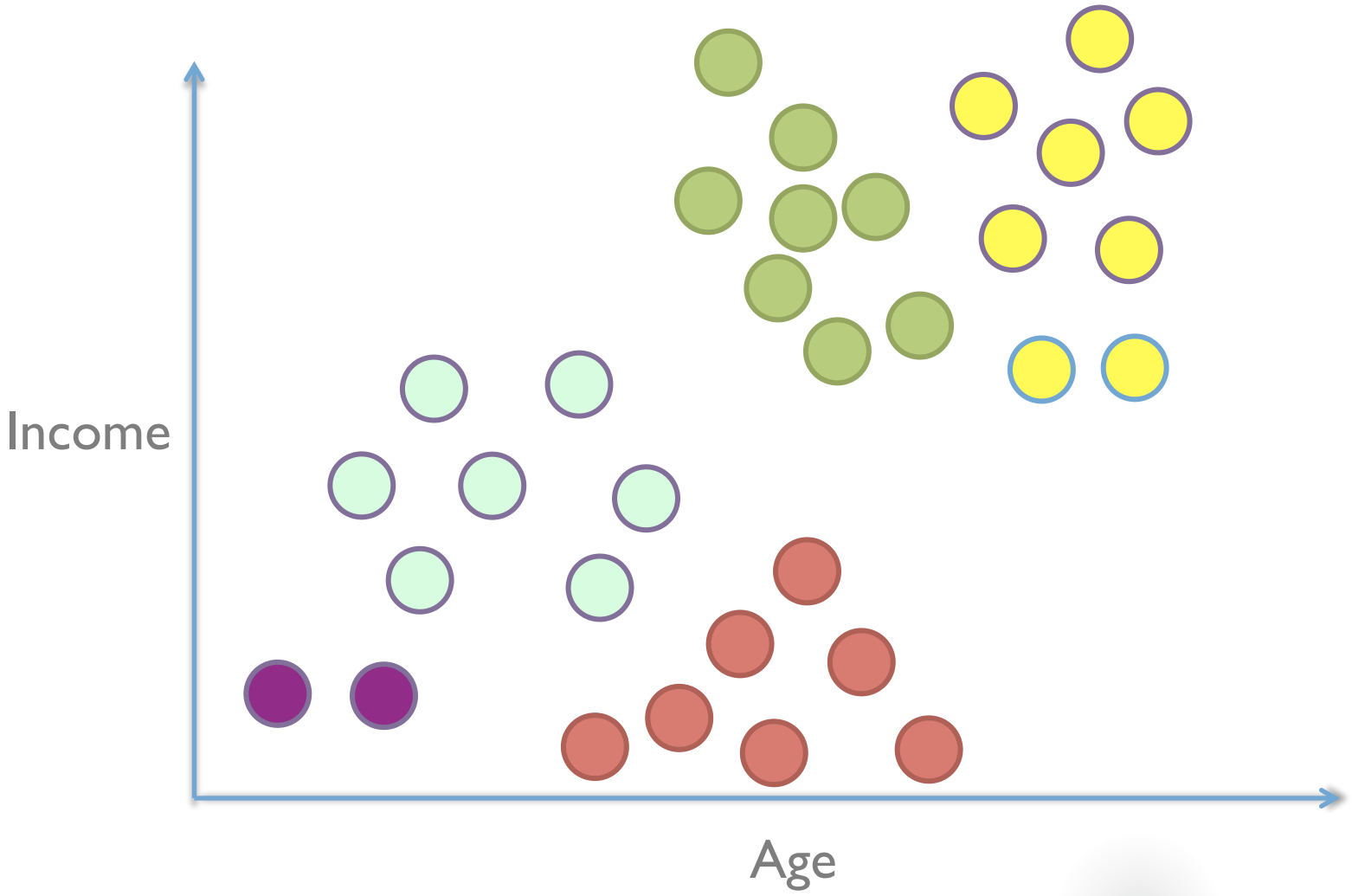


Agglomerative Hierarchical Clustering

Current num_clusters = 4

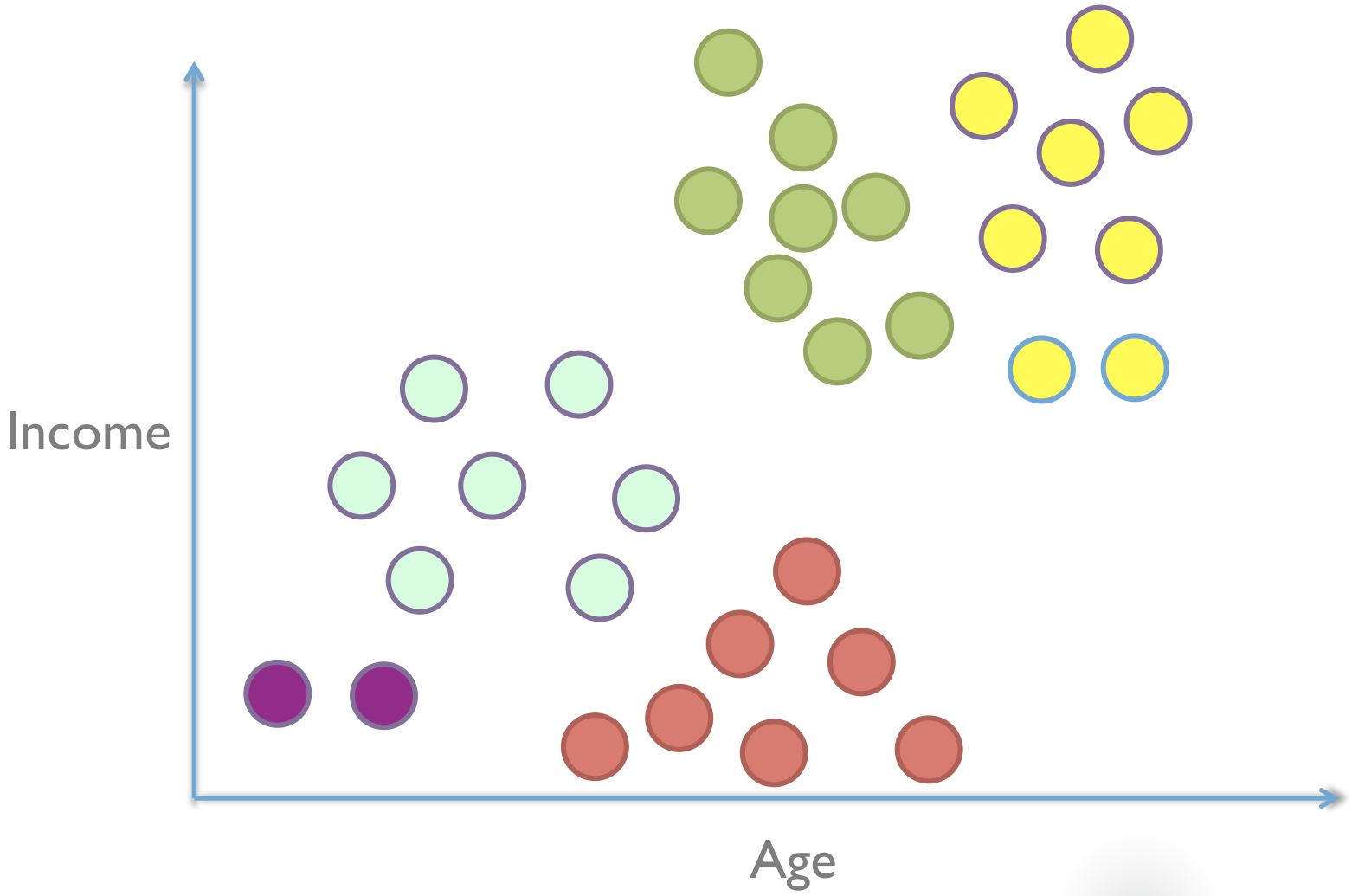
Agglomerative Hierarchical Clustering

Agglomerative Hierarchical Clustering

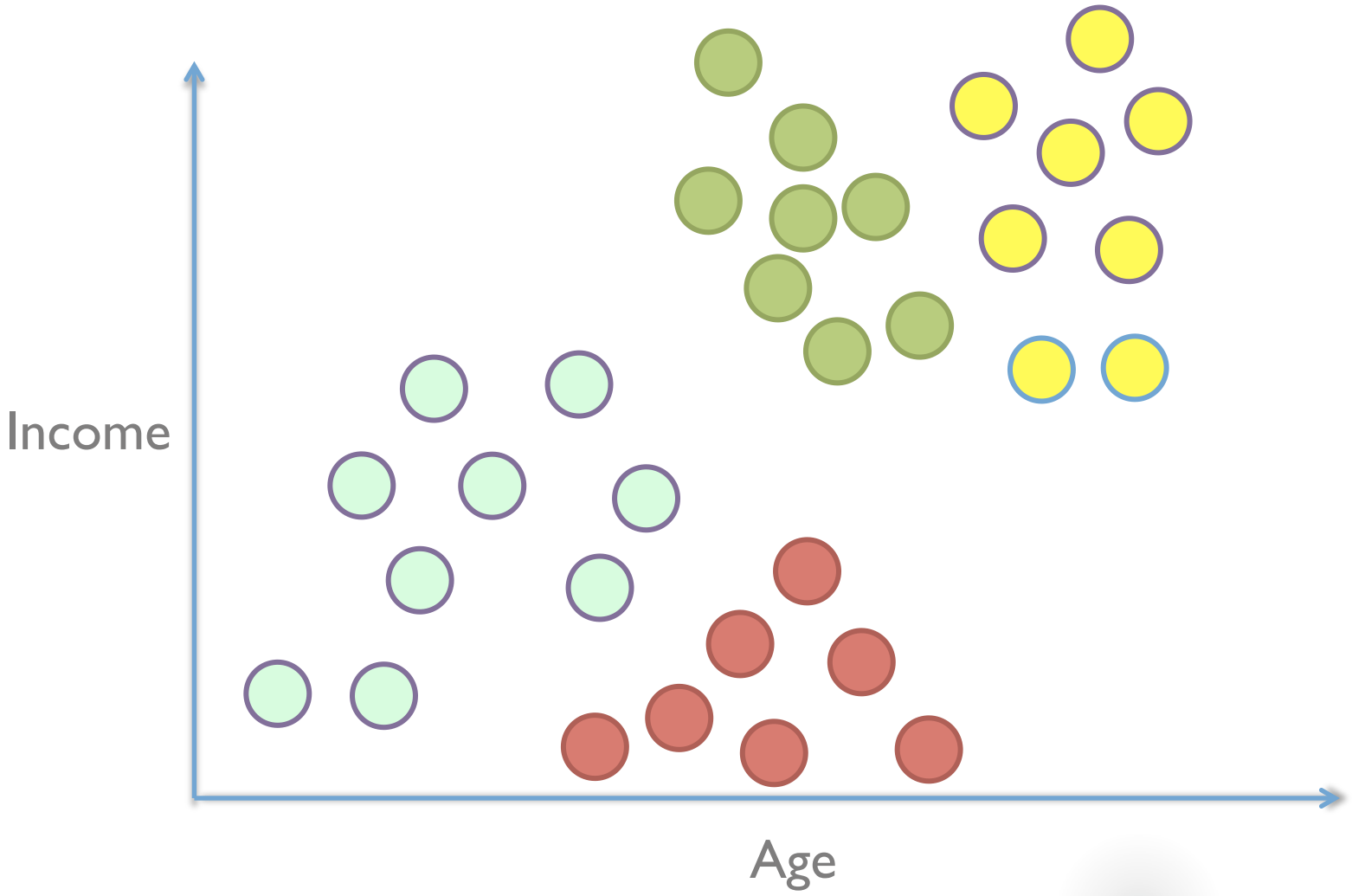


Agglomerative Hierarchical Clustering

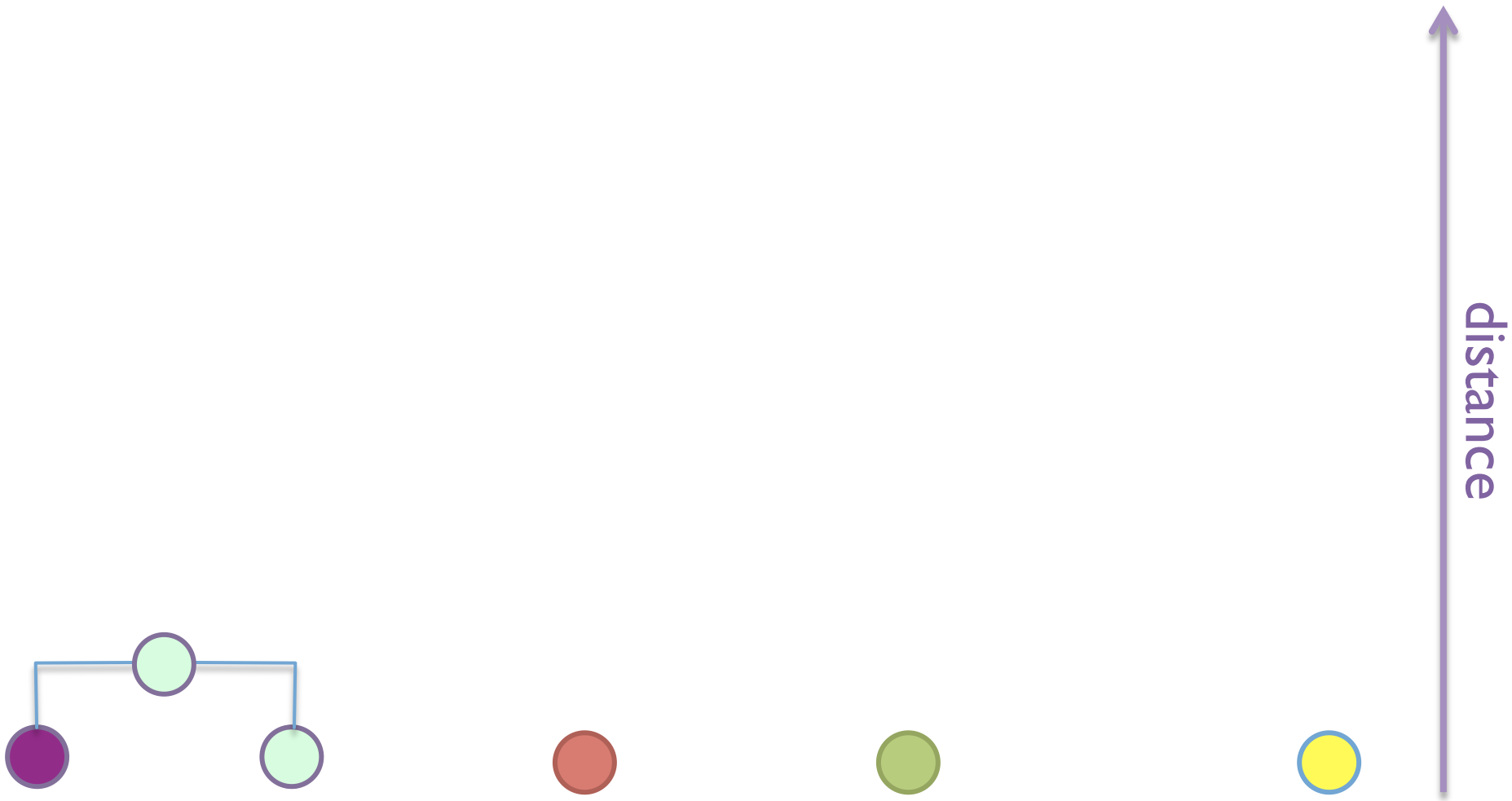
Agglomerative Hierarchical Clustering



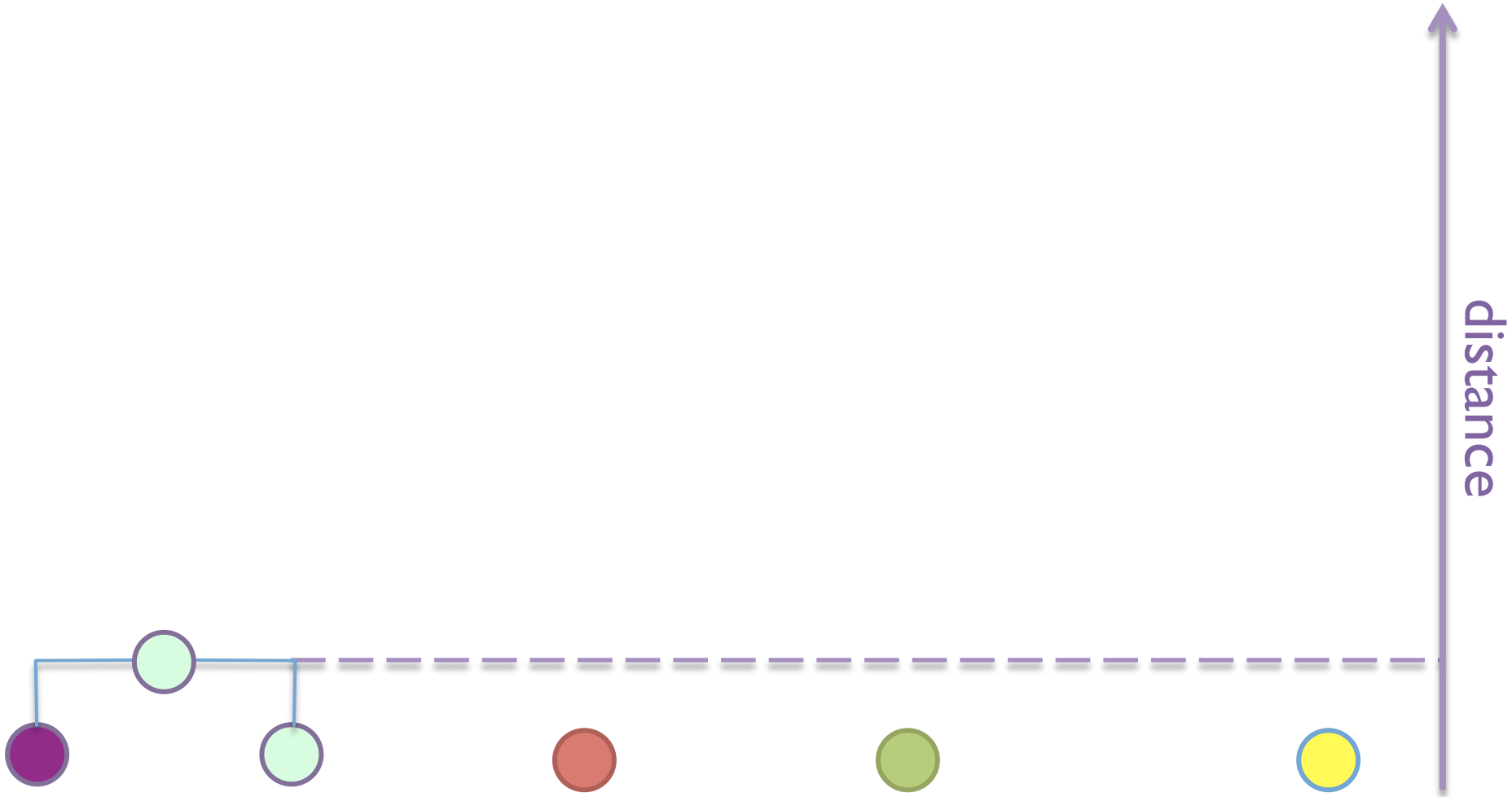
Agglomerative Hierarchical Clustering



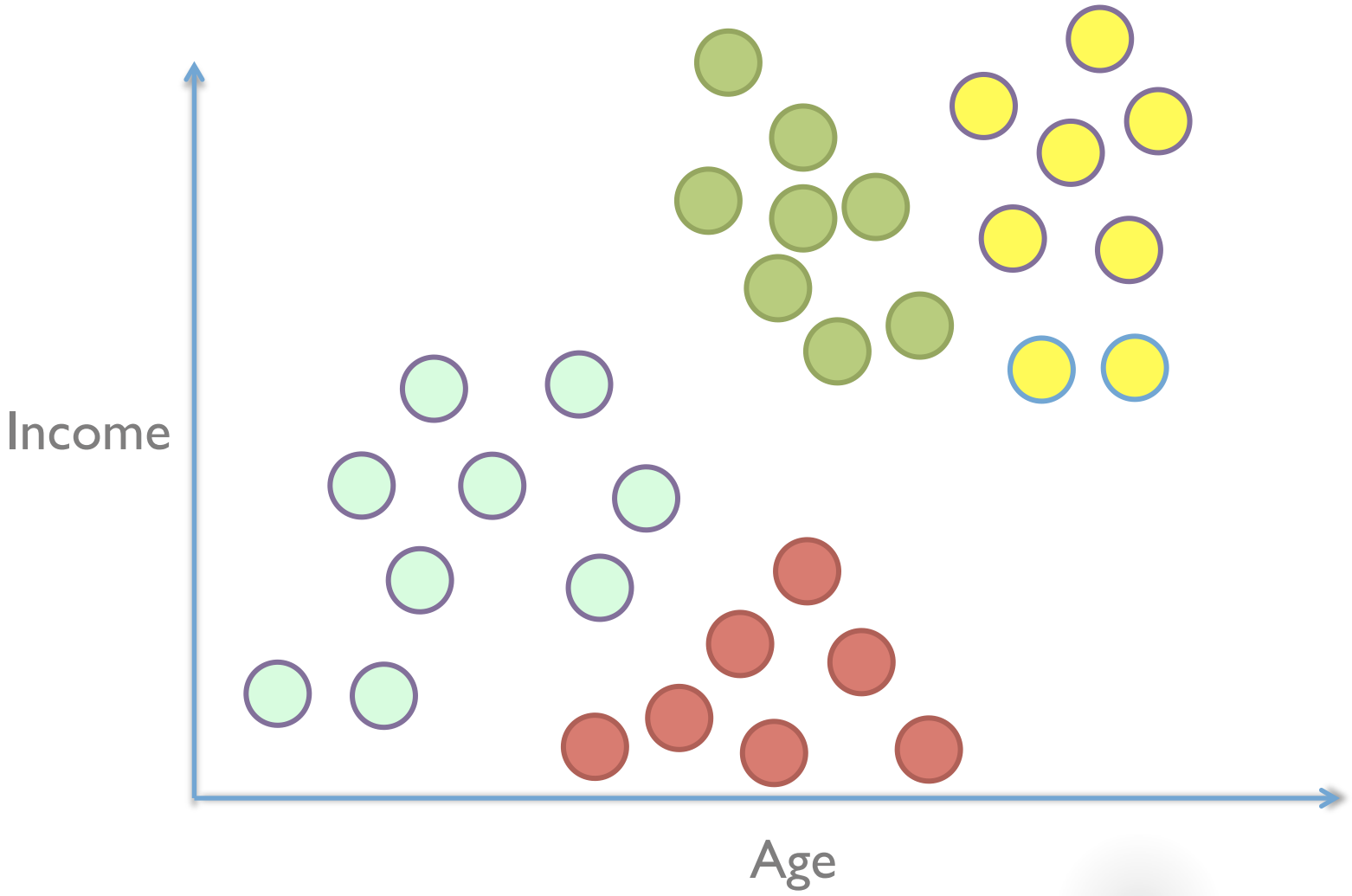
Agglomerative Hierarchical Clustering



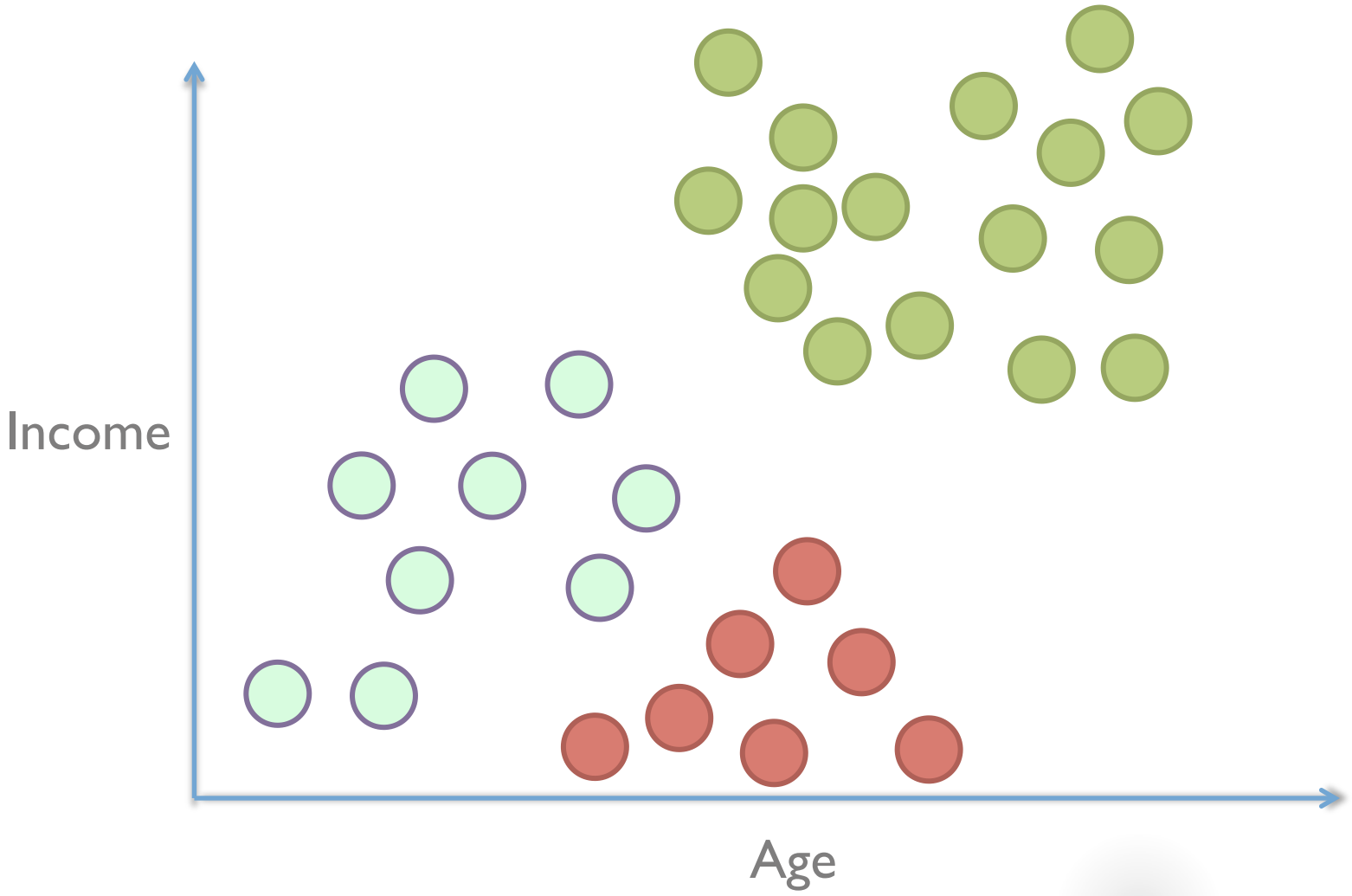
Agglomerative Hierarchical Clustering



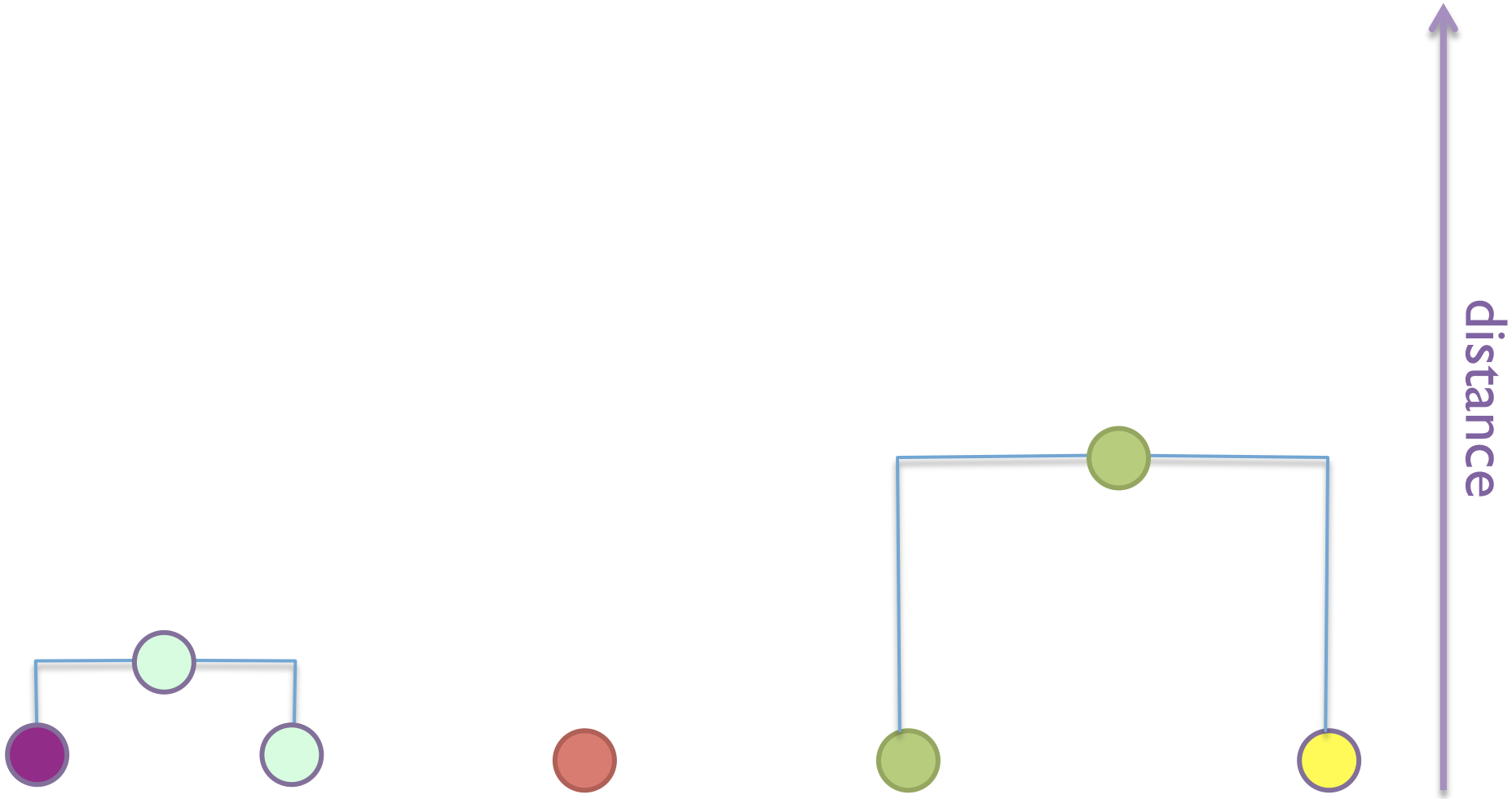
Agglomerative Hierarchical Clustering



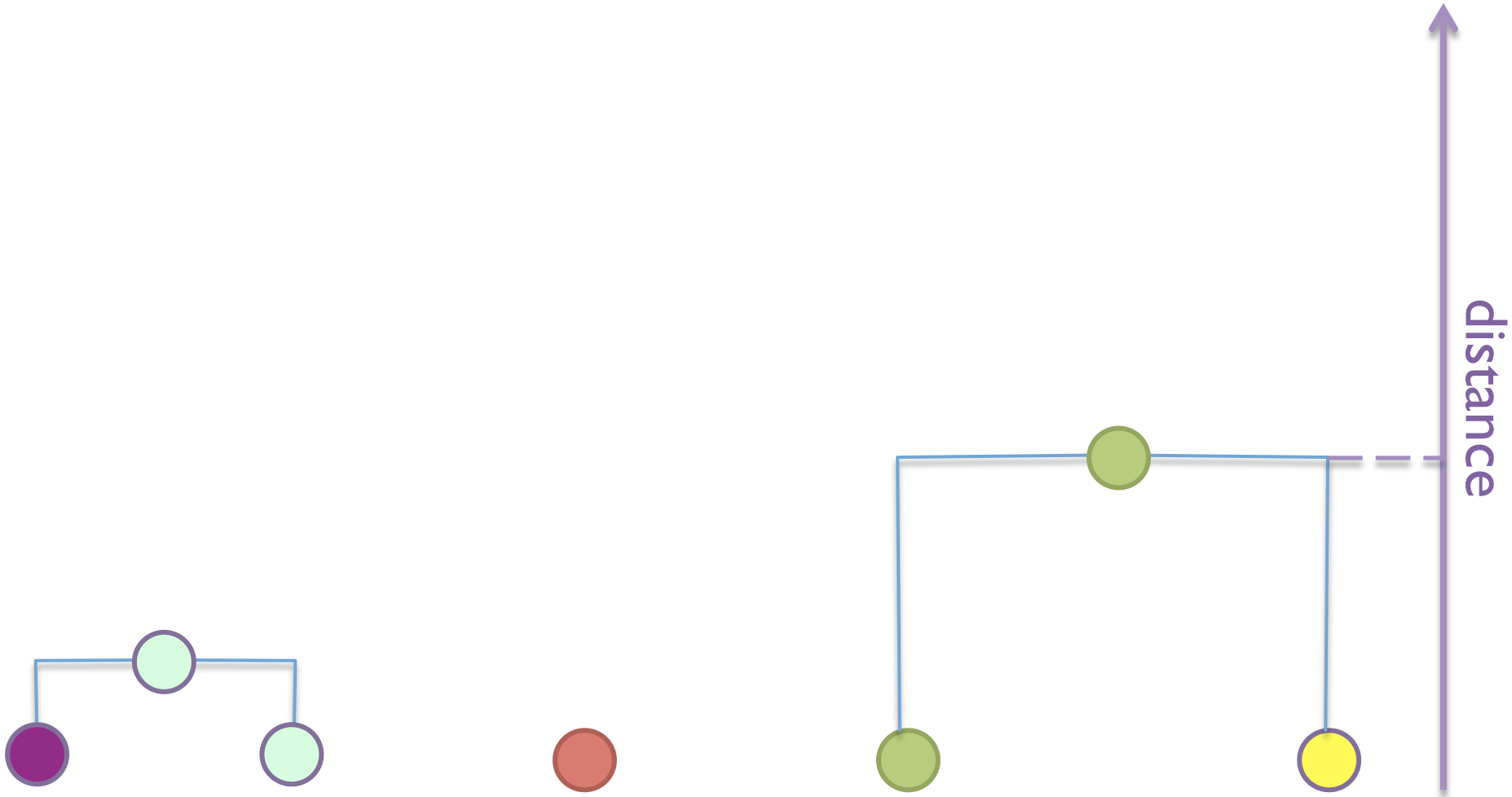
Agglomerative Hierarchical Clustering



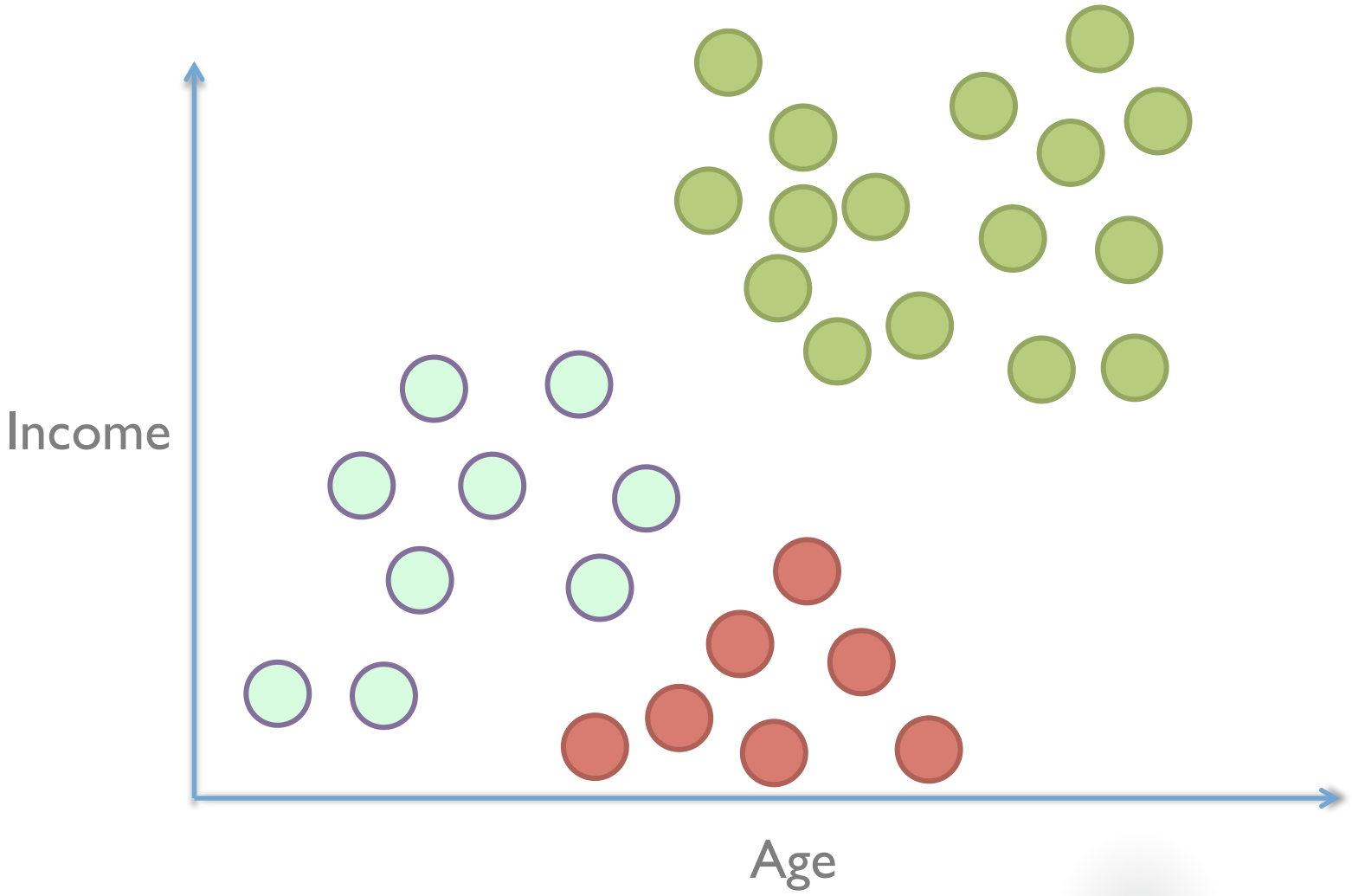
Agglomerative Hierarchical Clustering



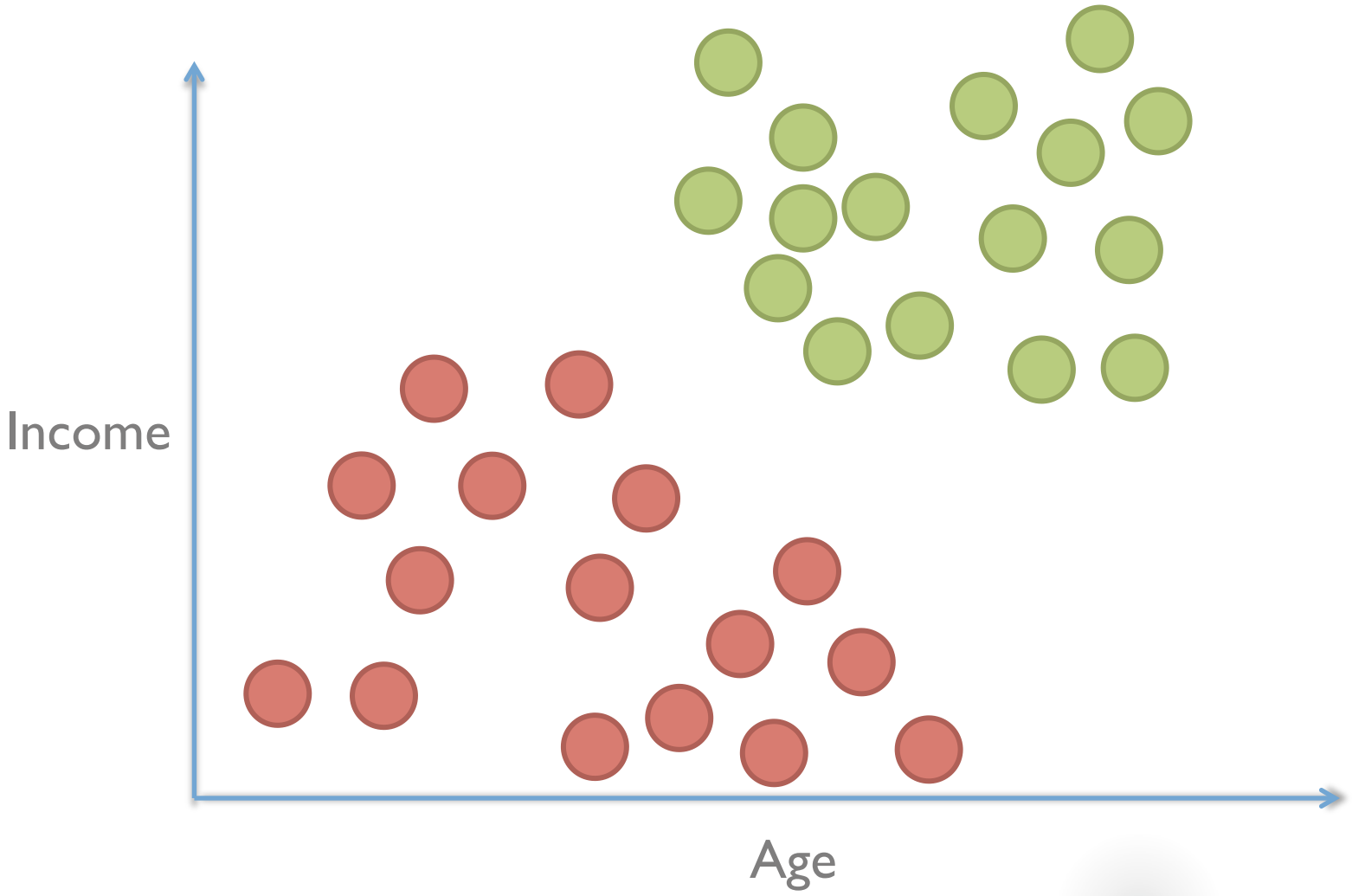
Agglomerative Hierarchical Clustering



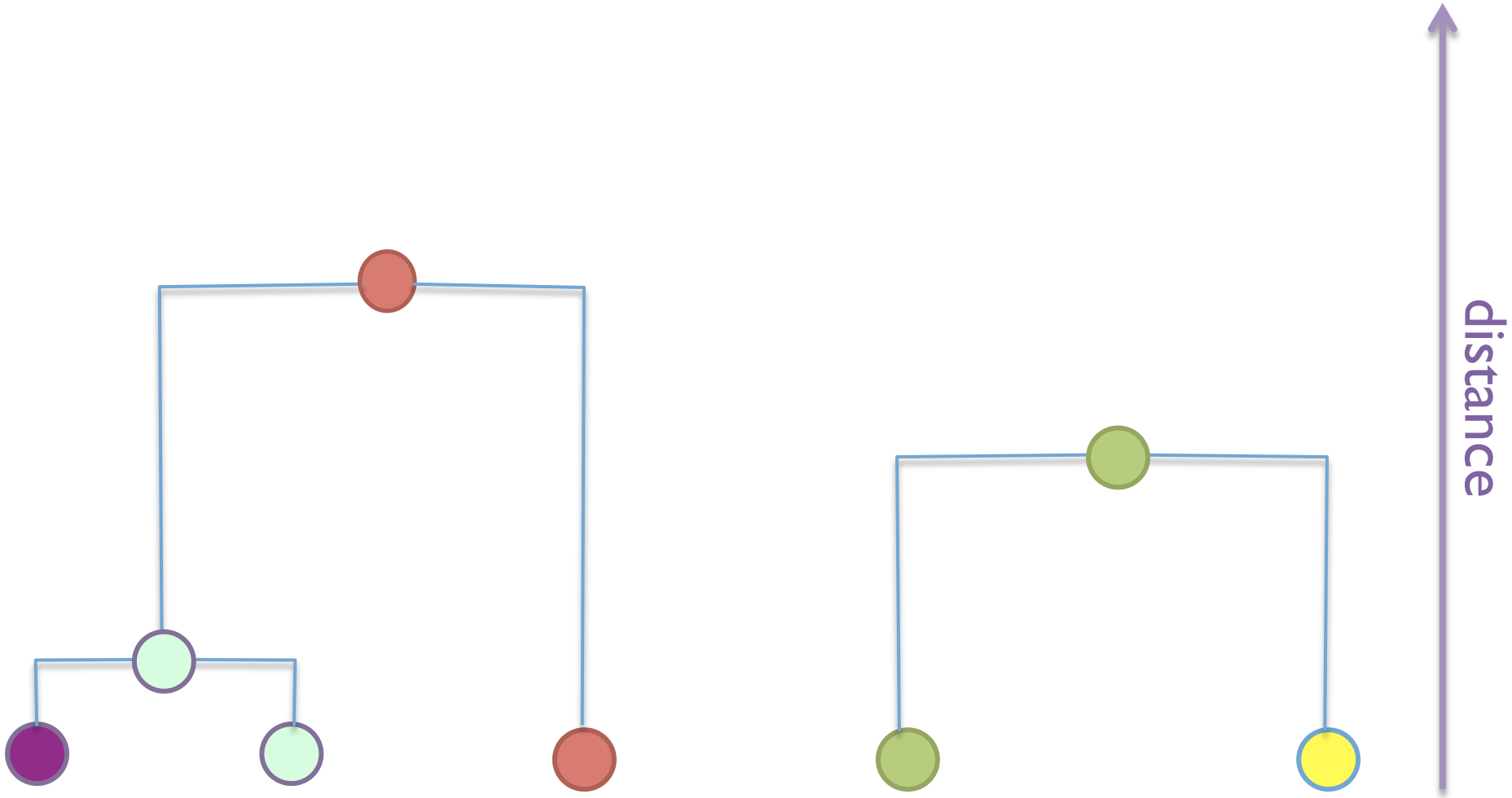
Agglomerative Hierarchical Clustering



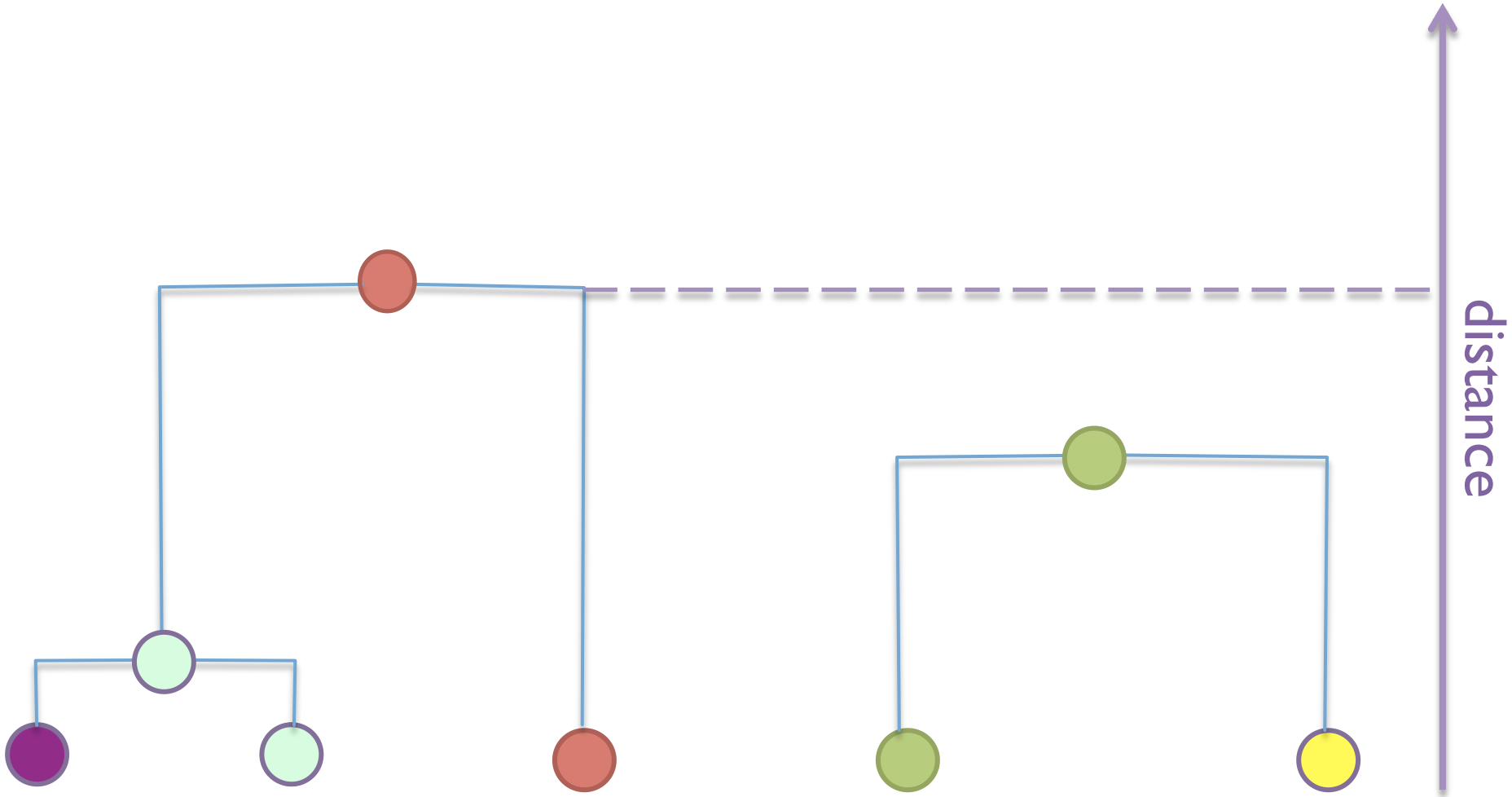
Agglomerative Hierarchical Clustering



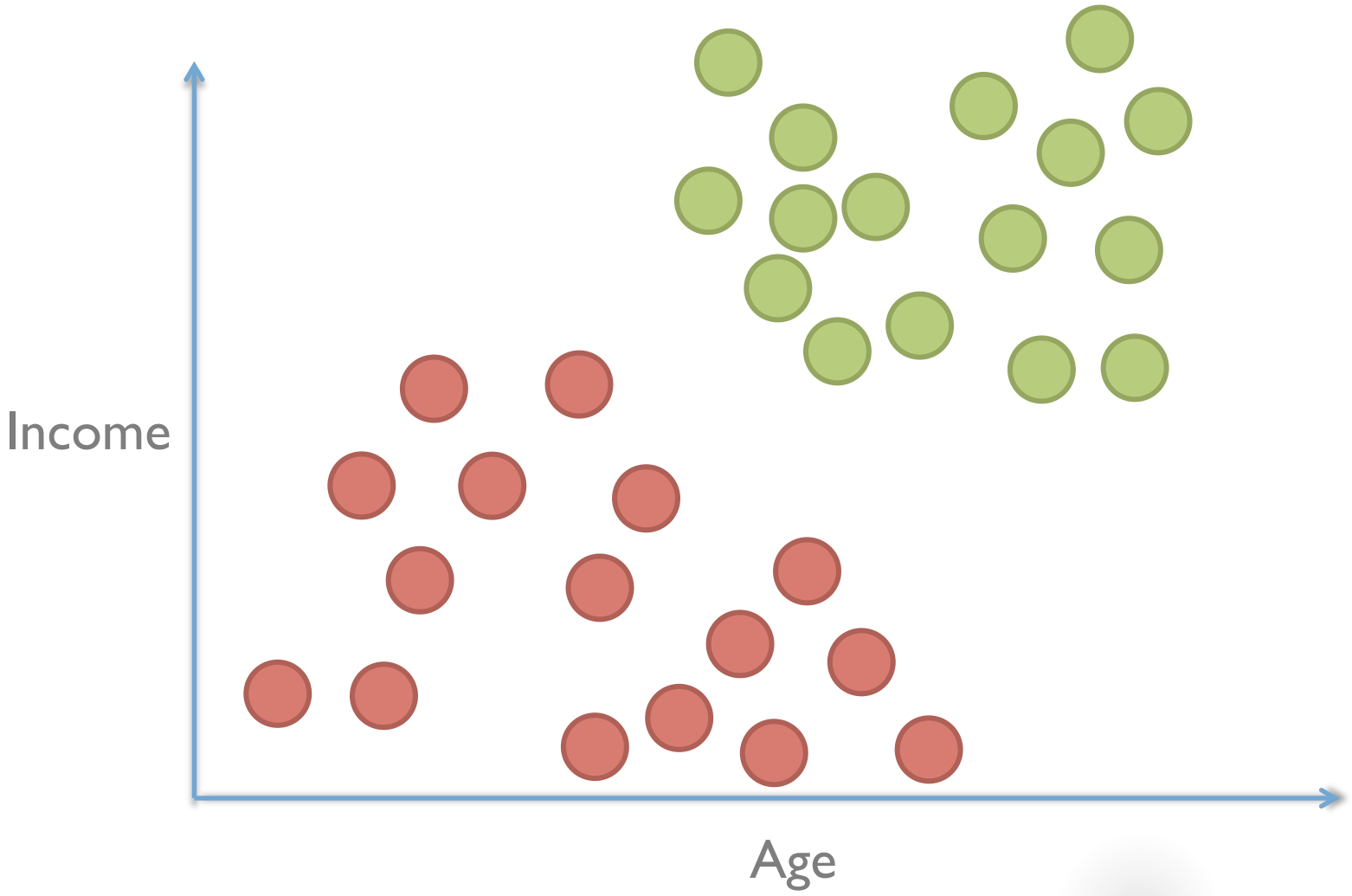
Agglomerative Hierarchical Clustering



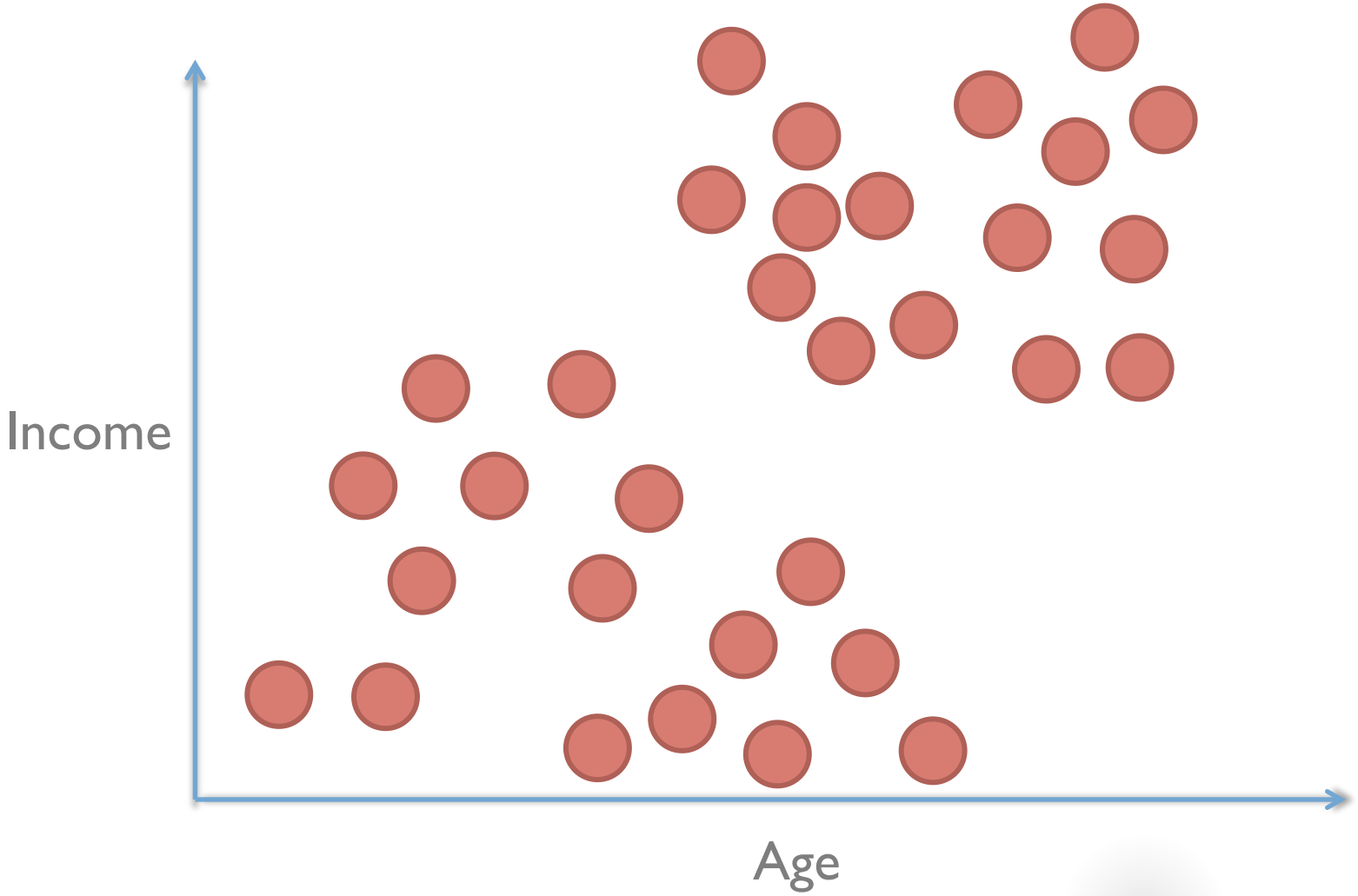
Agglomerative Hierarchical Clustering



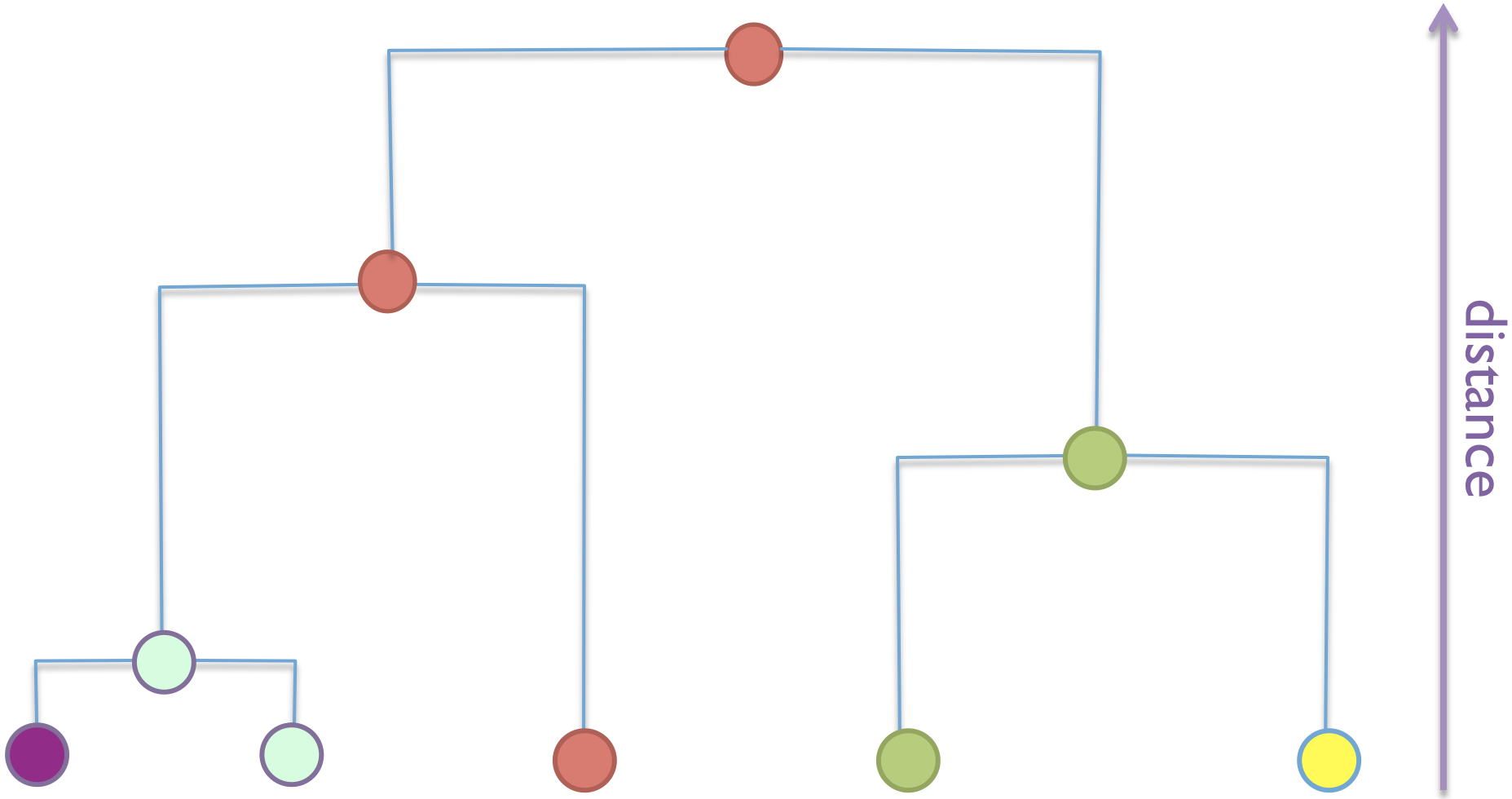
Agglomerative Hierarchical Clustering



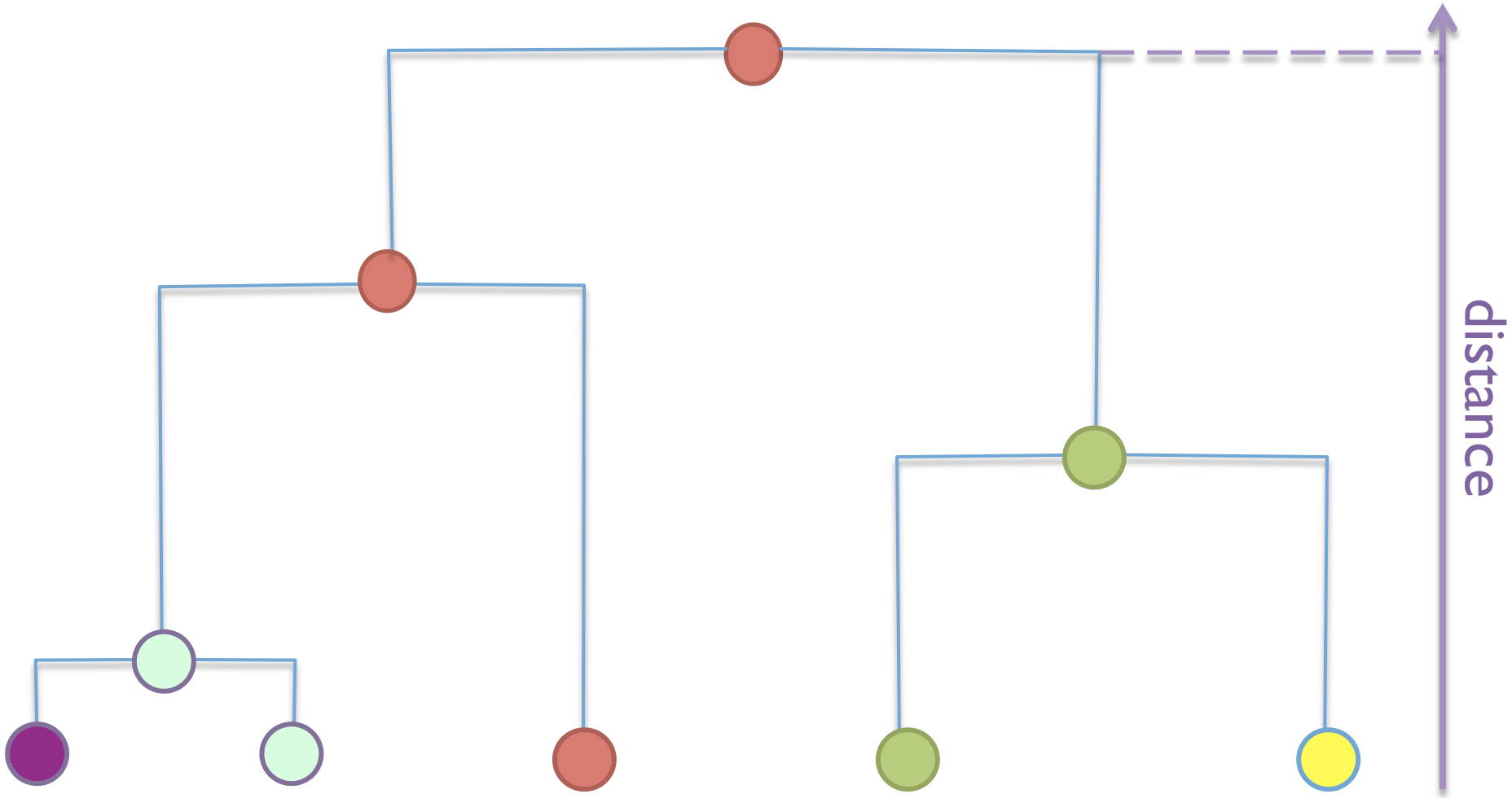
Agglomerative Hierarchical Clustering



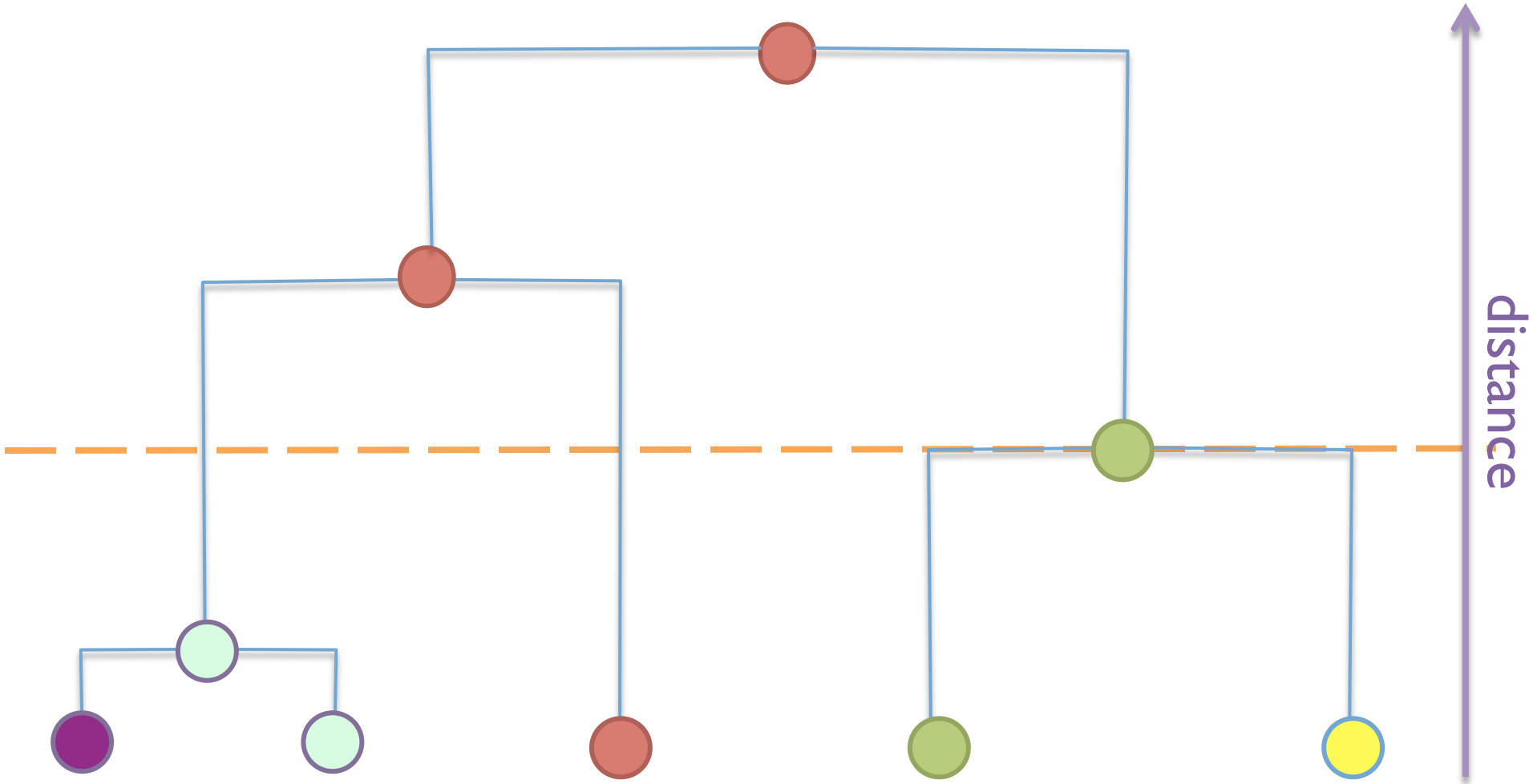
Agglomerative Hierarchical Clustering



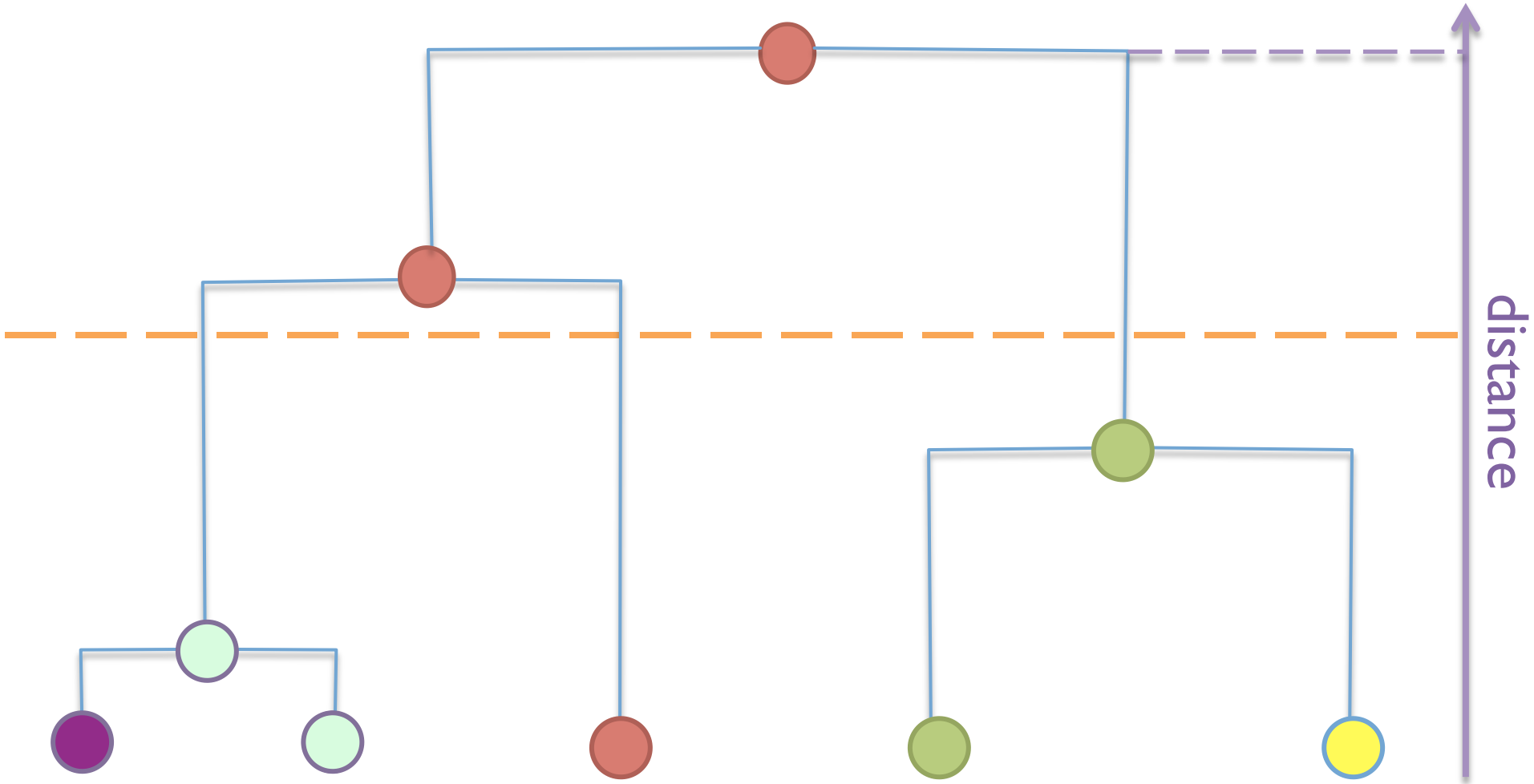
Agglomerative Hierarchical Clustering



Criterion: Stop at k=3 clusters!



Criterion: Stop at dist=3……!



```
from sklearn.cluster import
AgglomerativeClustering

AgglomerativeClustering(….,
                        ….
                         ,
                        linkage = “ward”,
                        ….
                         ,
                        affinity = “euclidian”,
                        ….
                         )
```

```
from sklearn.cluster import
AgglomerativeClustering

AgglomerativeClustering(….,
                        ….,
                        linkage = “ward”,
                        ….,
                        affinity = “euclidian”,
                        ….)
```

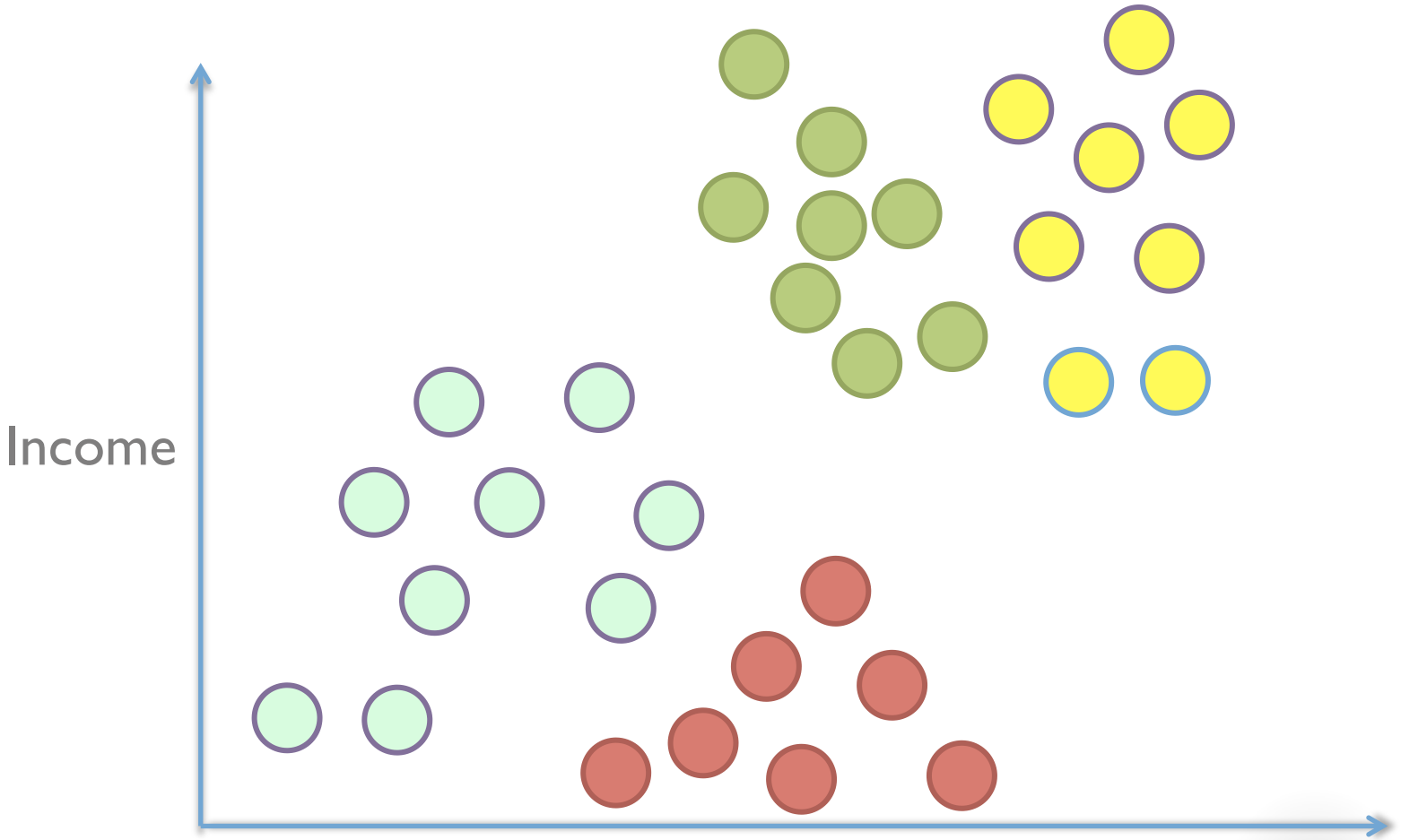
Agglomerative Clustering linkage

Which clusters to merge next.

Definition of “shortest distance”

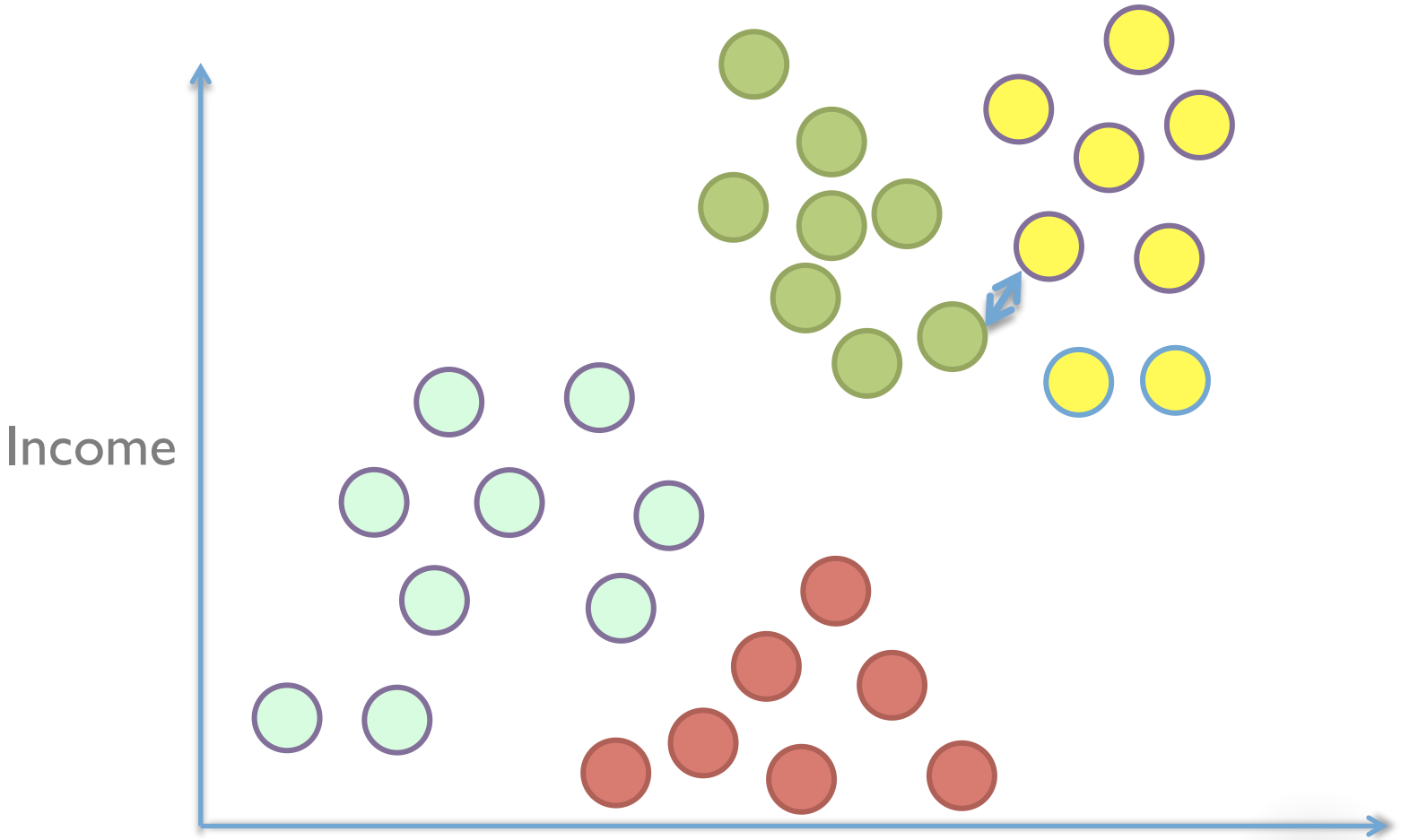
linkage = “single”

Distance between two cluster is the minimum pairwise distance



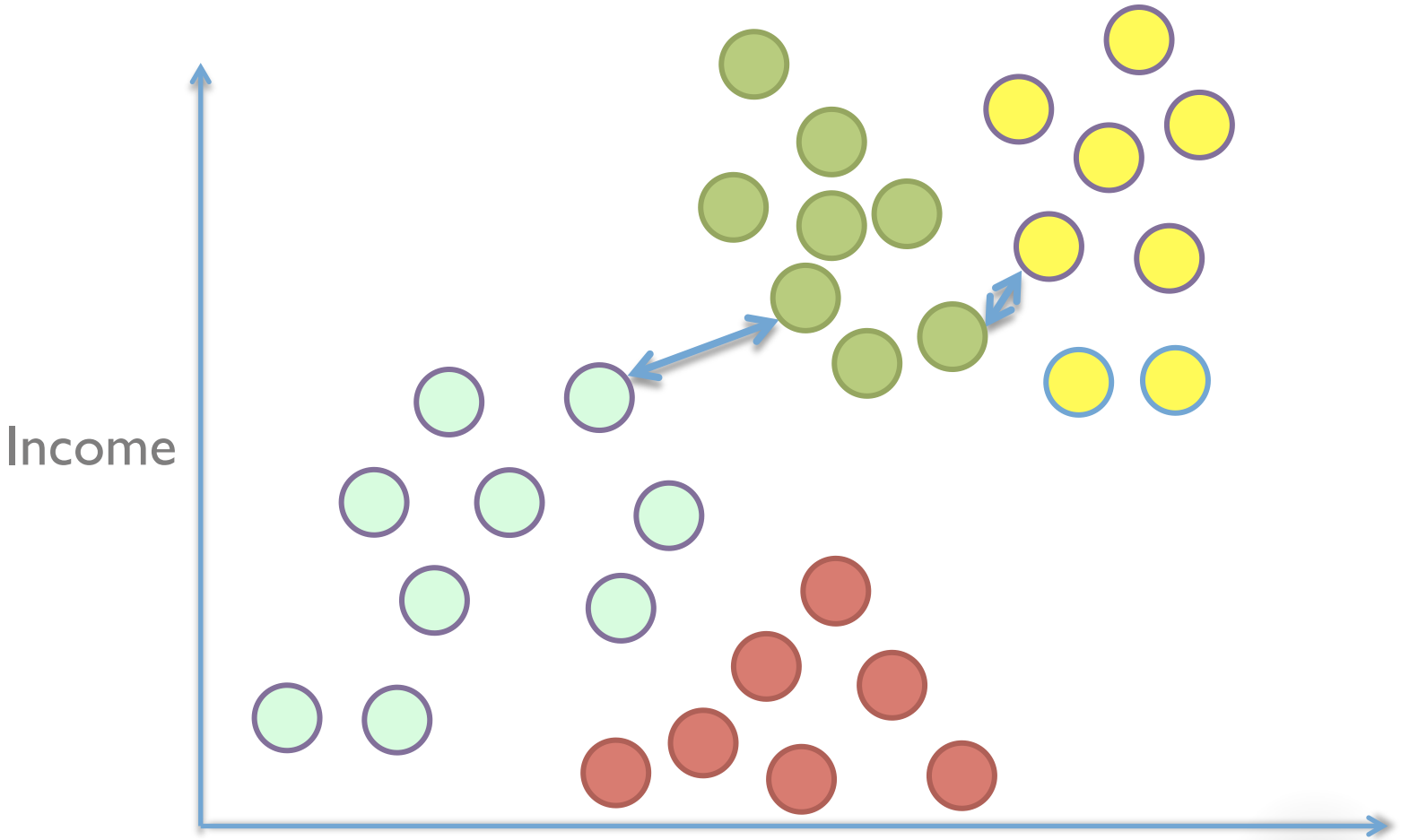
linkage = “single”

Distance between two cluster is the minimum pairwise distance



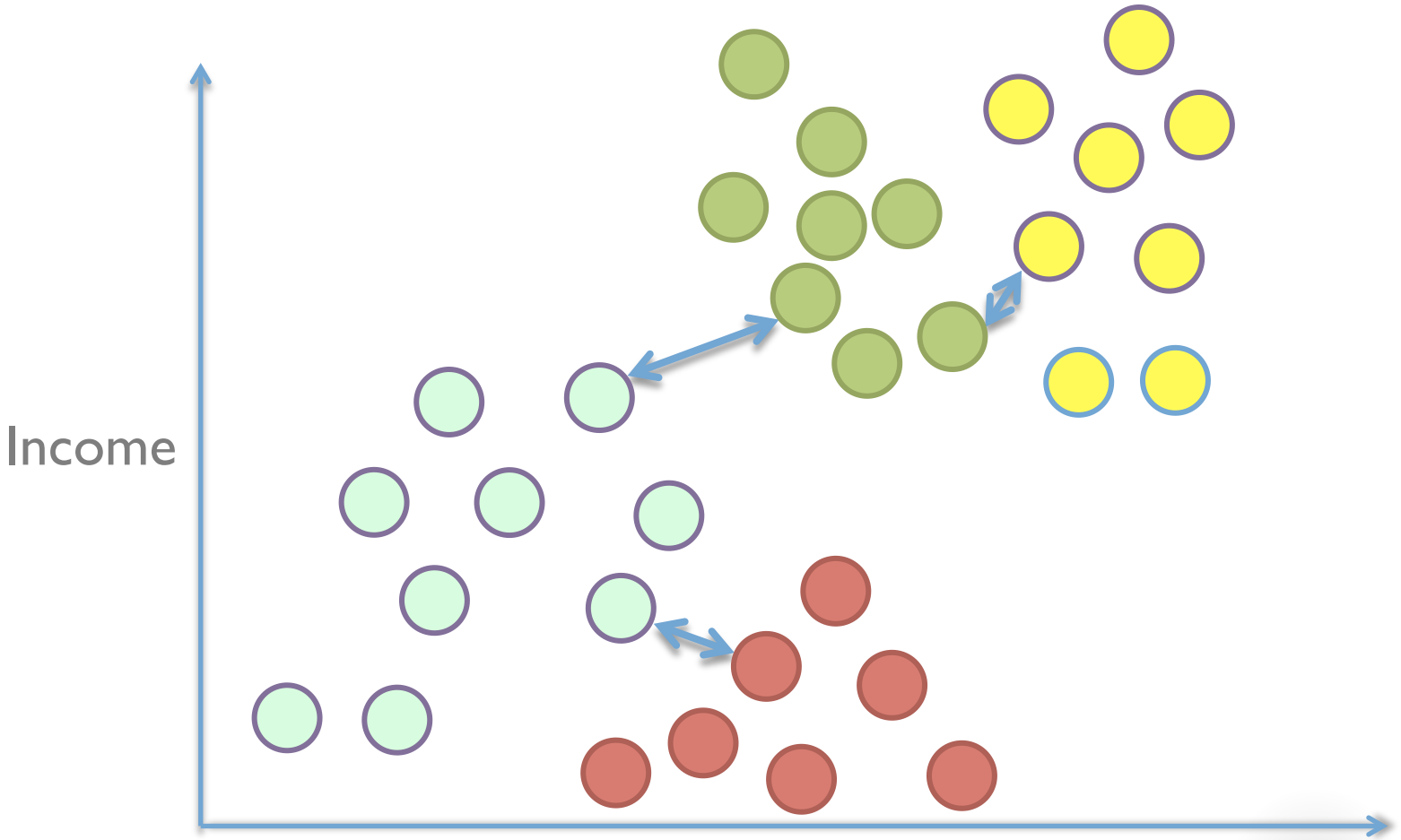
linkage = “single”

Distance between two cluster is the minimum pairwise distance



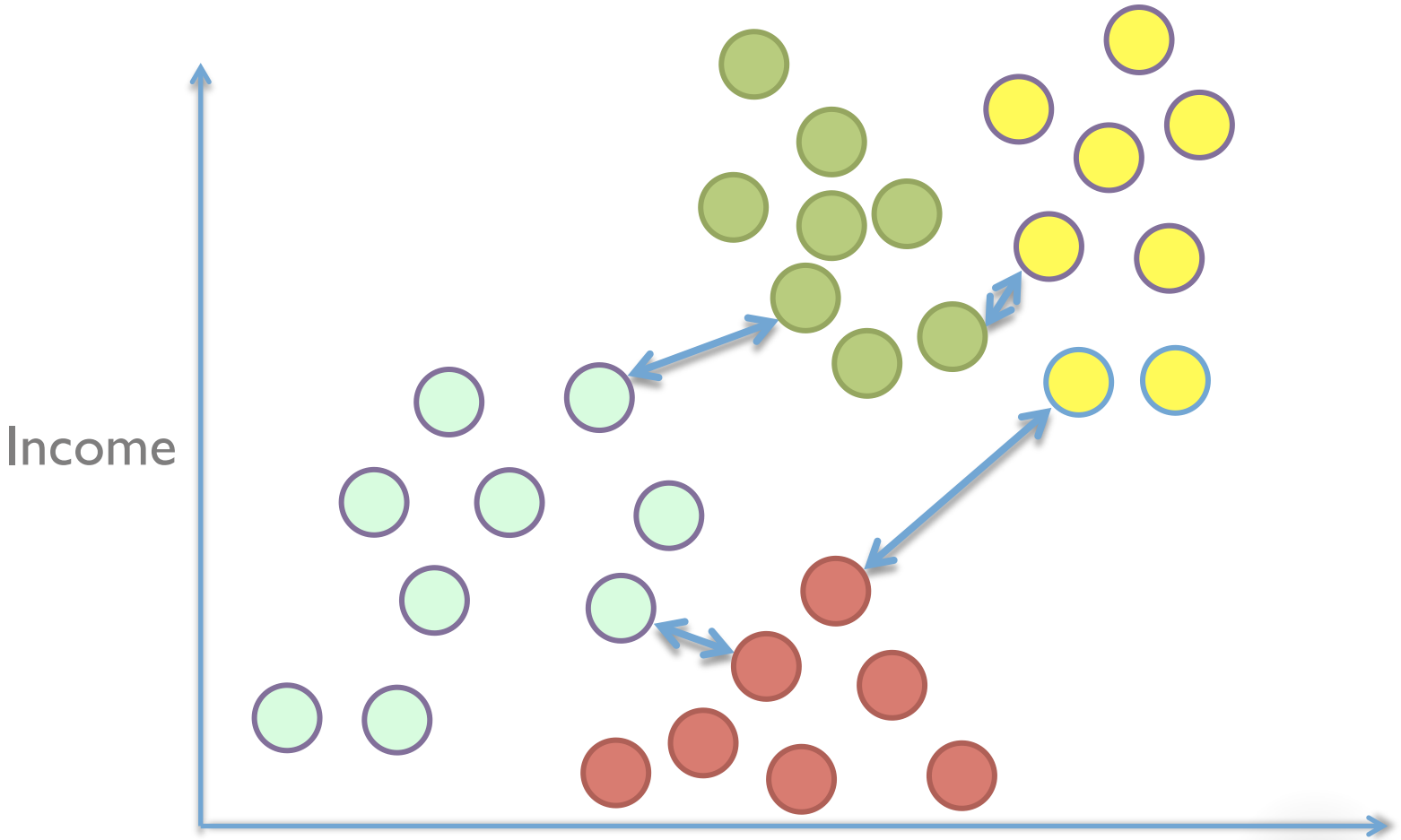
linkage = “single”

Distance between two cluster is the minimum pairwise distance



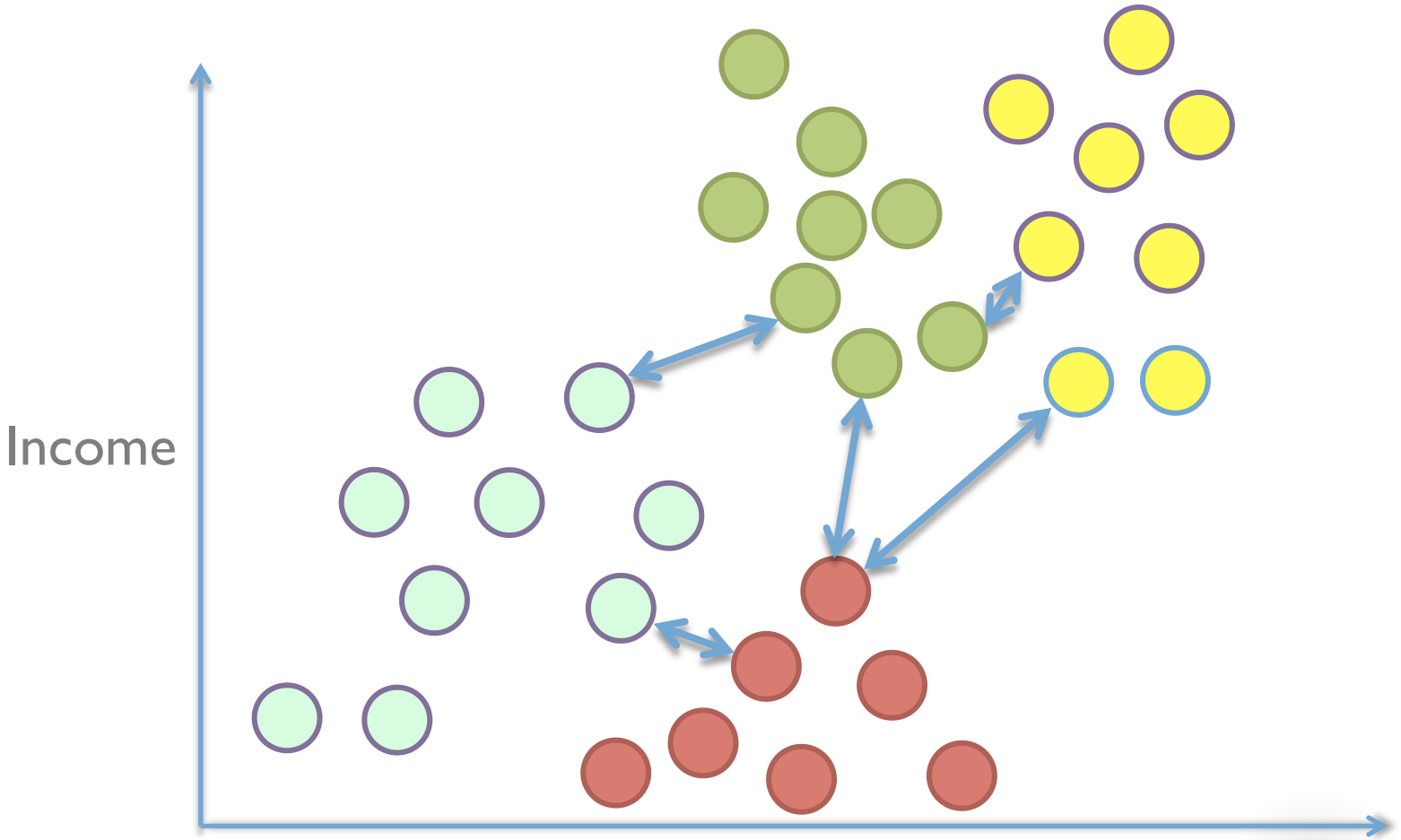
linkage = “single”

Distance between two cluster is the minimum pairwise distance



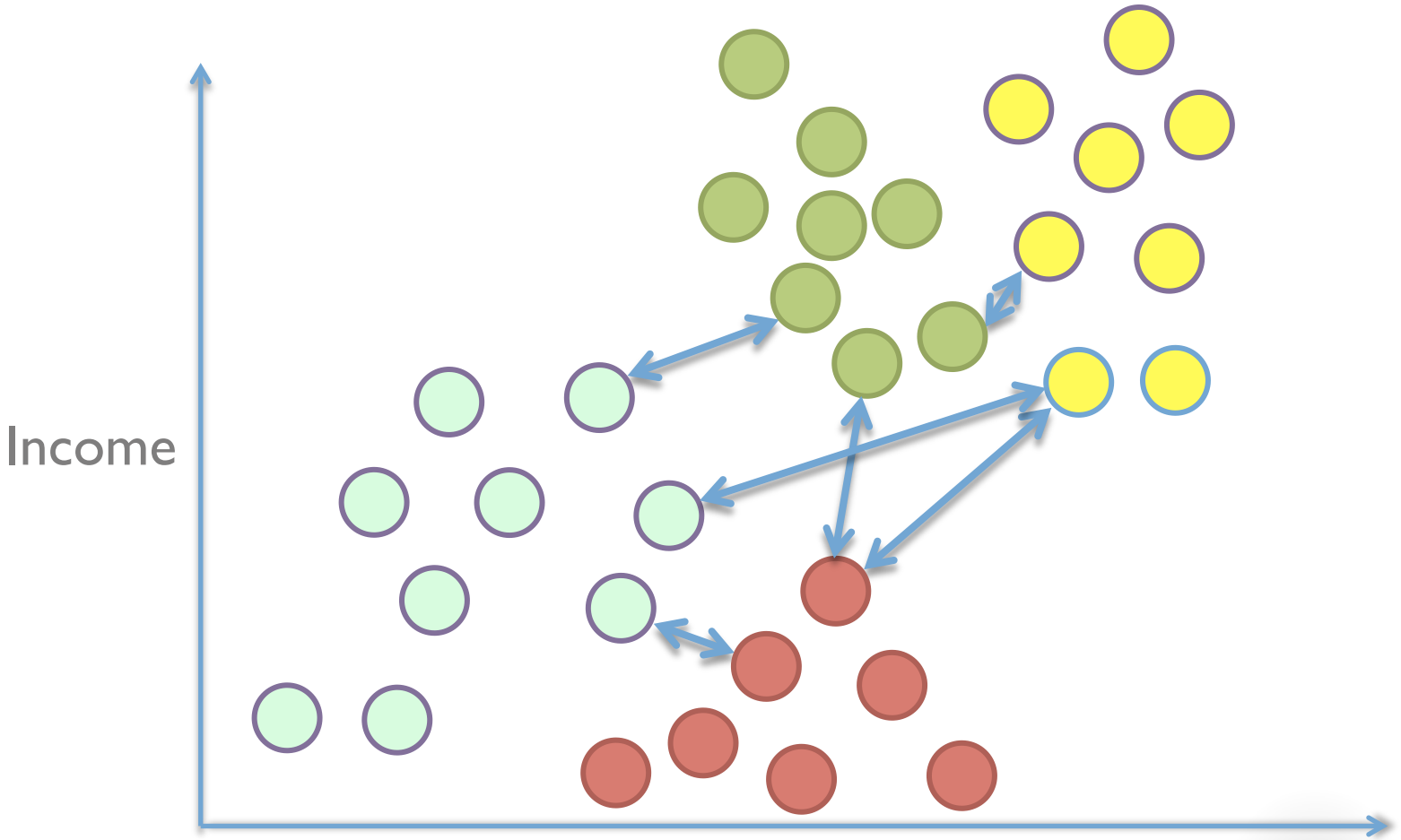
linkage = “single”

Distance between two cluster is the minimum pairwise distance



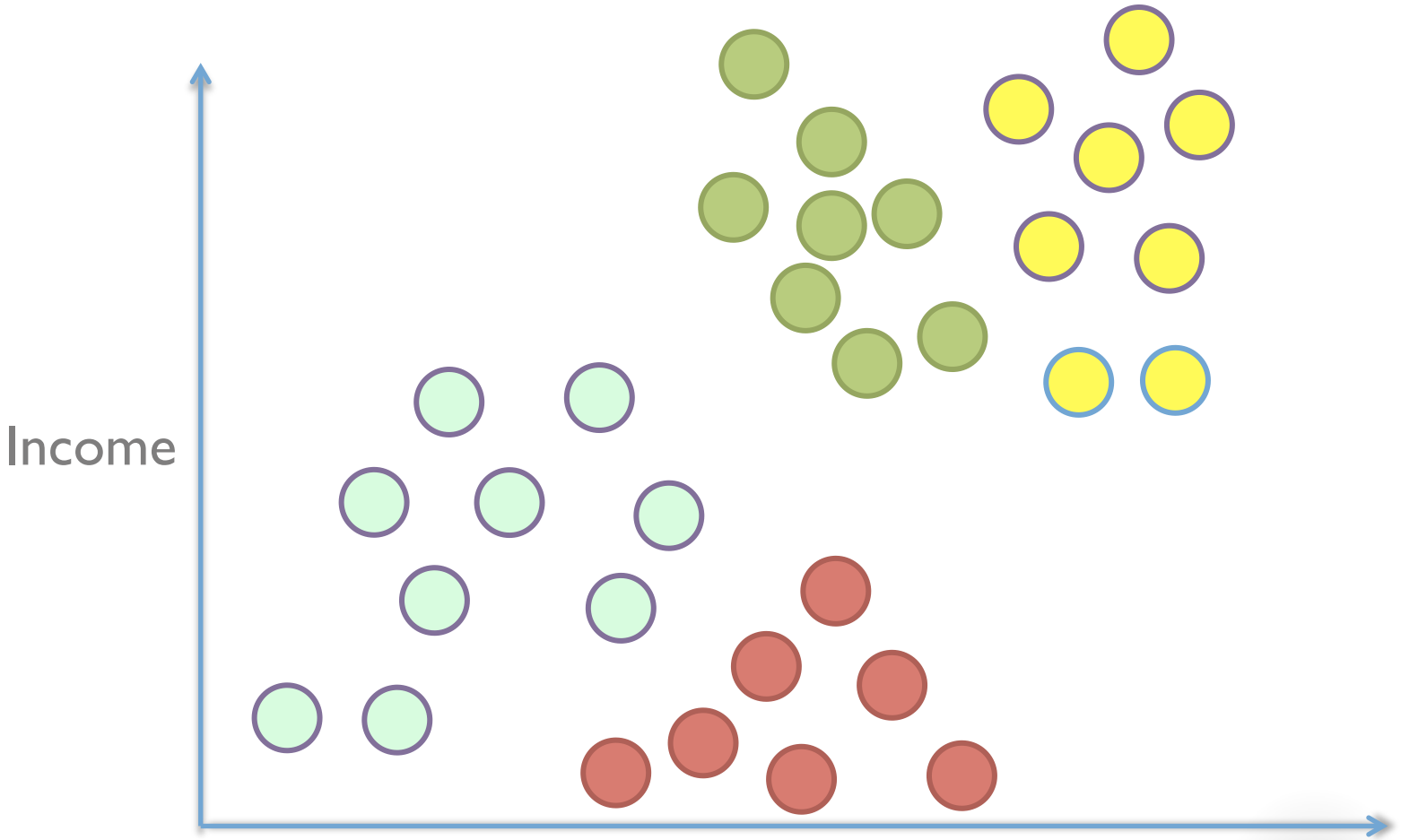
linkage = “single”

Fast. Can from long chains instead of clusters.



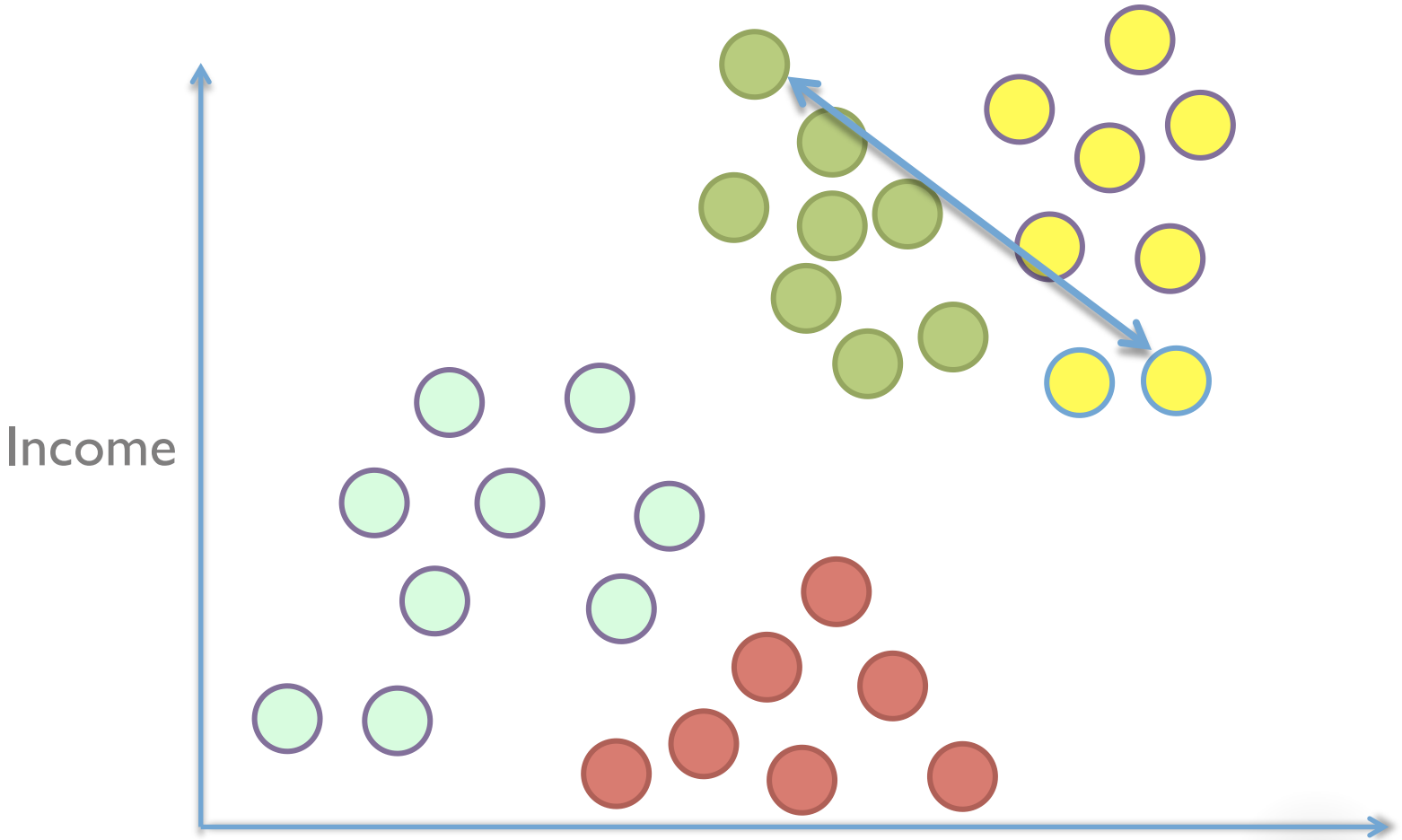
linkage = “complete”

Distance between two clusters is the maximum pairwise distance



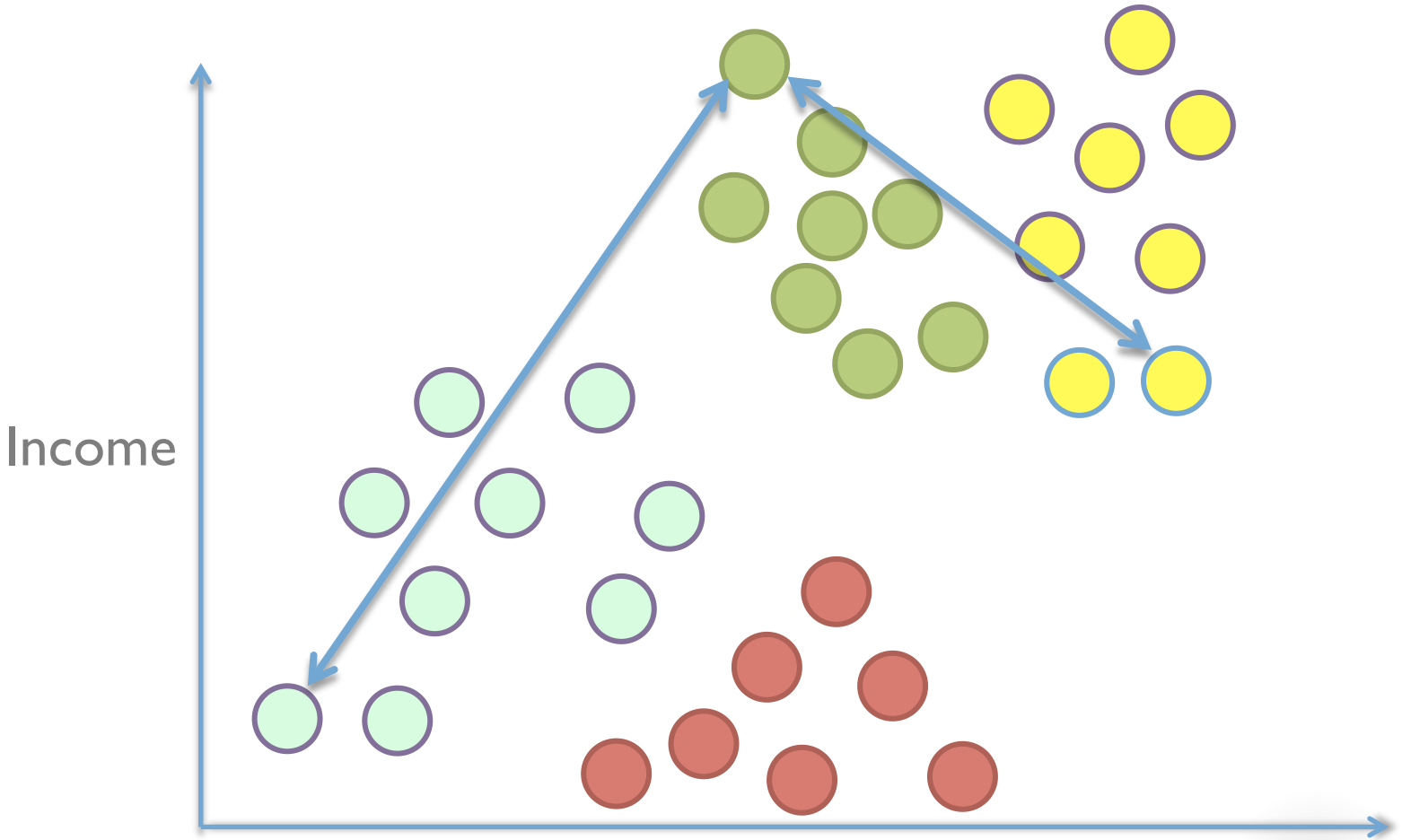
linkage = “complete”

Distance between two clusters is the maximum pairwise distance



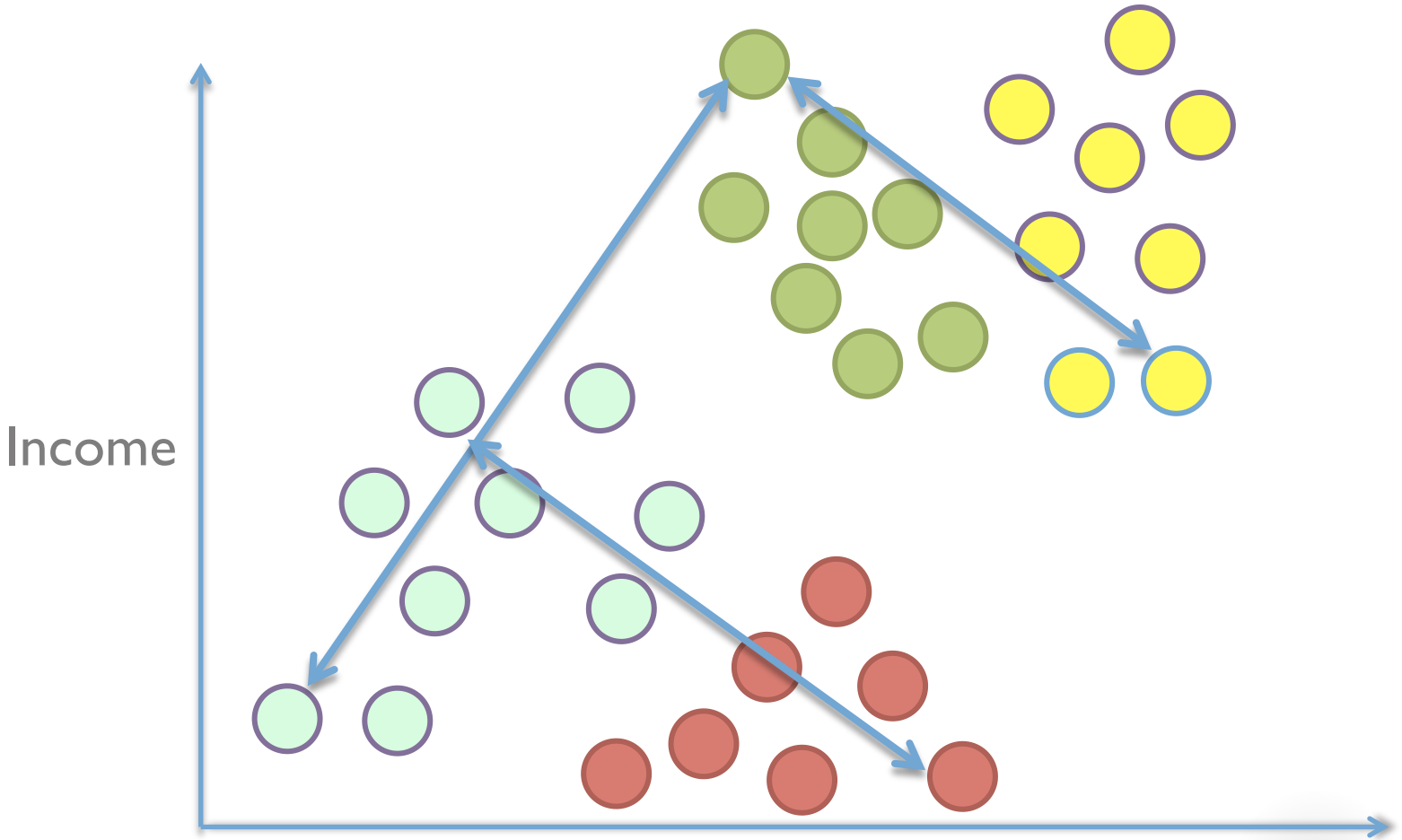
linkage = “complete”

Distance between two clusters is the maximum pairwise distance



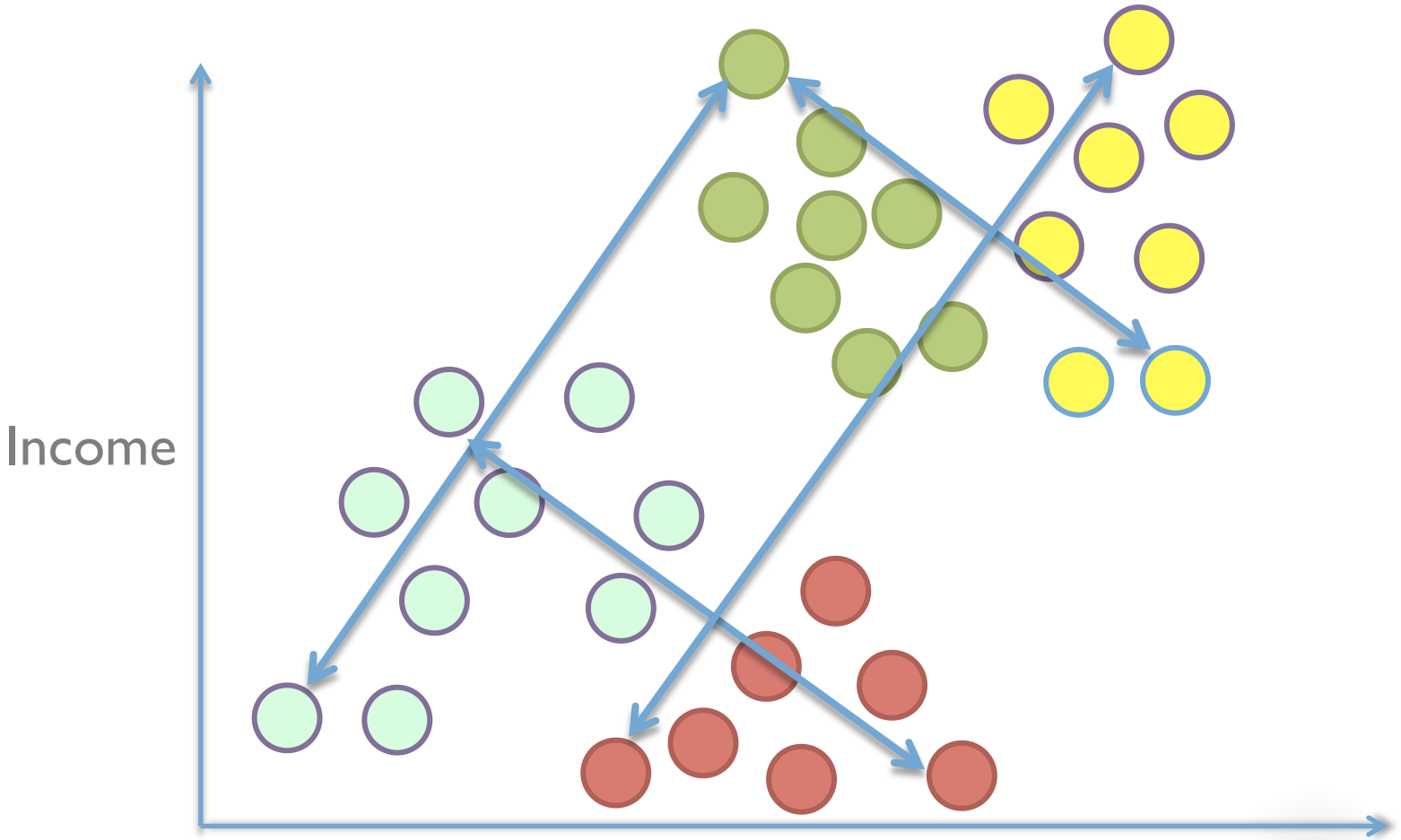
linkage = “complete”

Distance between two clusters is the maximum pairwise distance



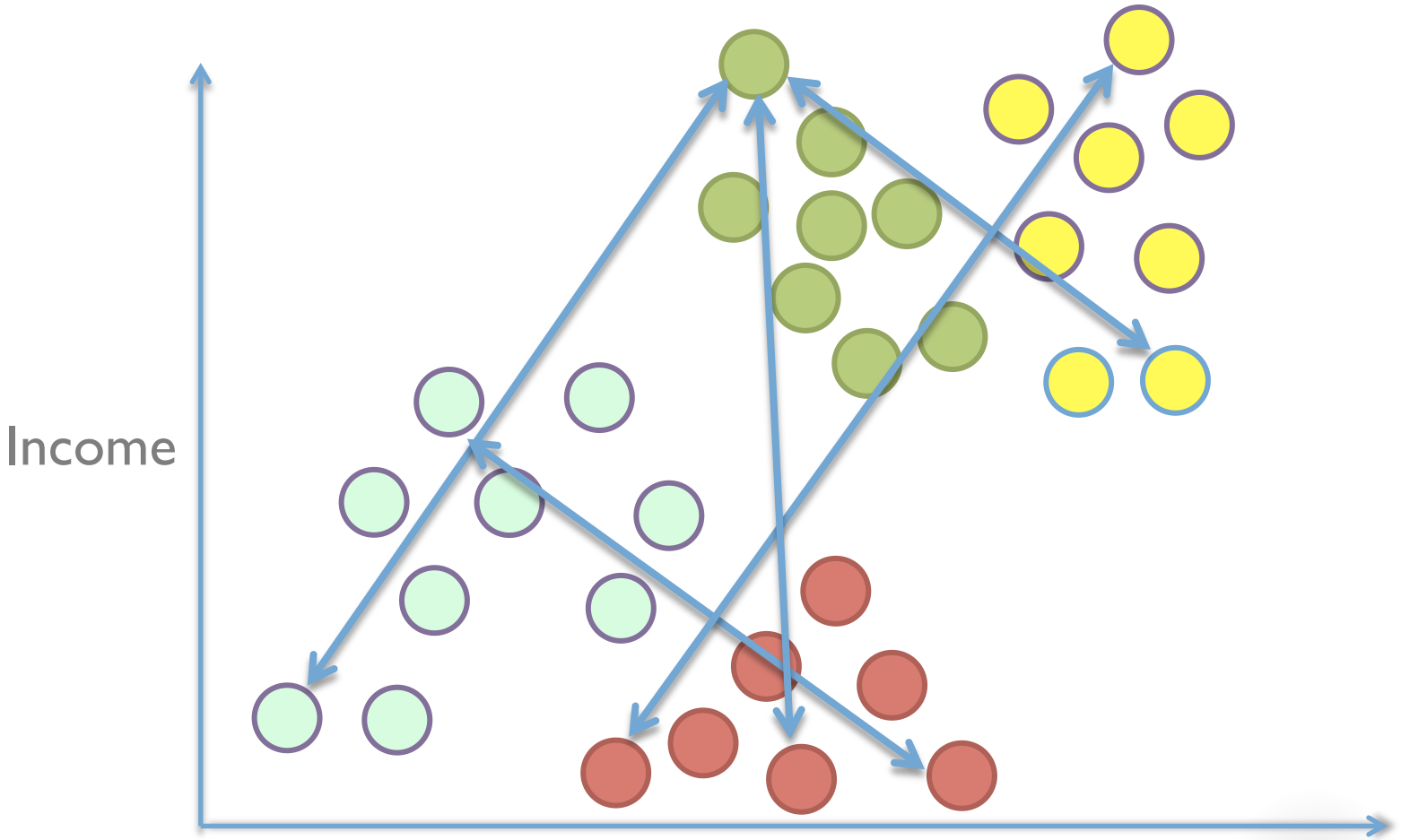
linkage = “complete”

Distance between two clusters is the maximum pairwise distance



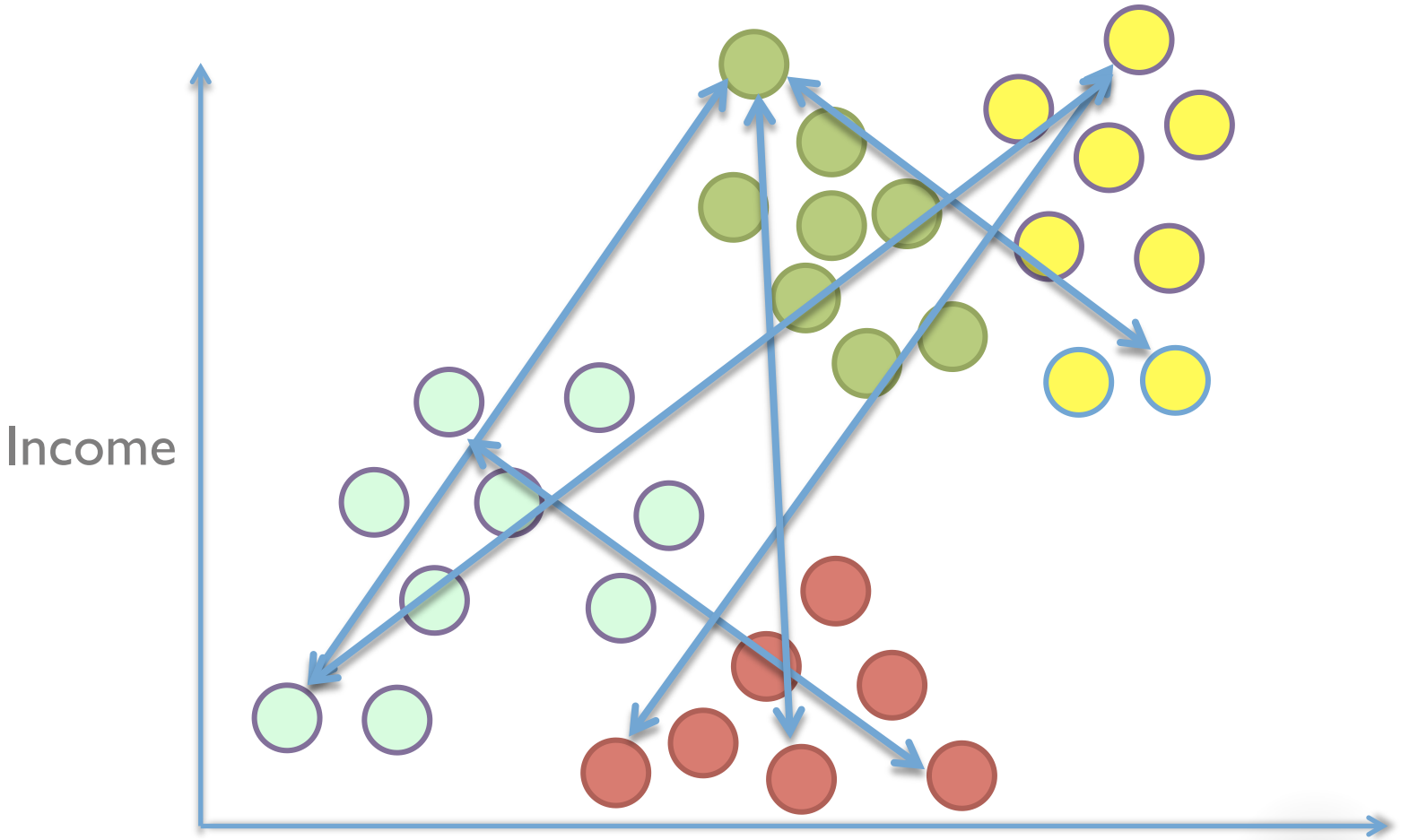
linkage = “complete”

Distance between two clusters is the maximum pairwise distance



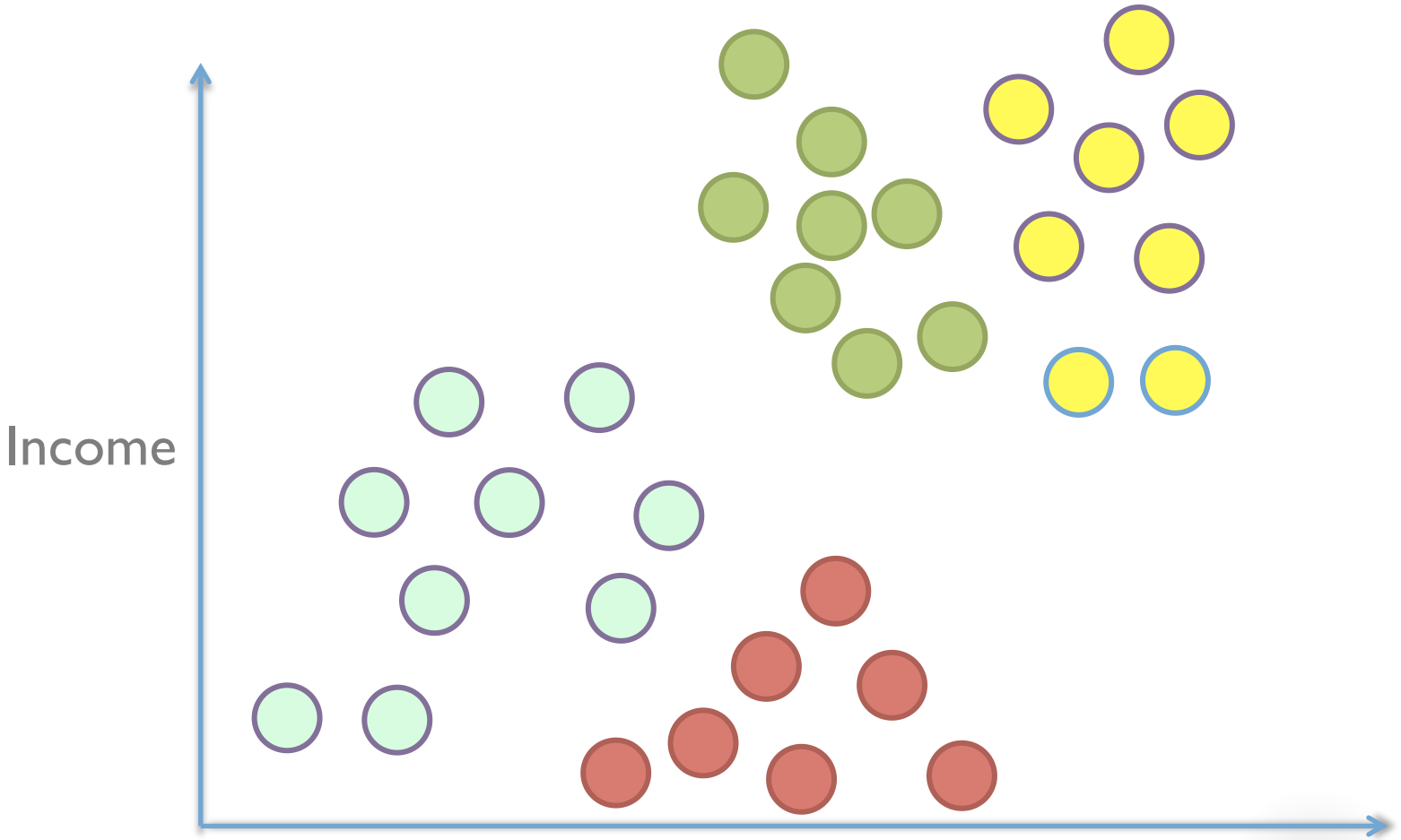
linkage = “complete”

Fast. No chains. Sensitive to outliers.



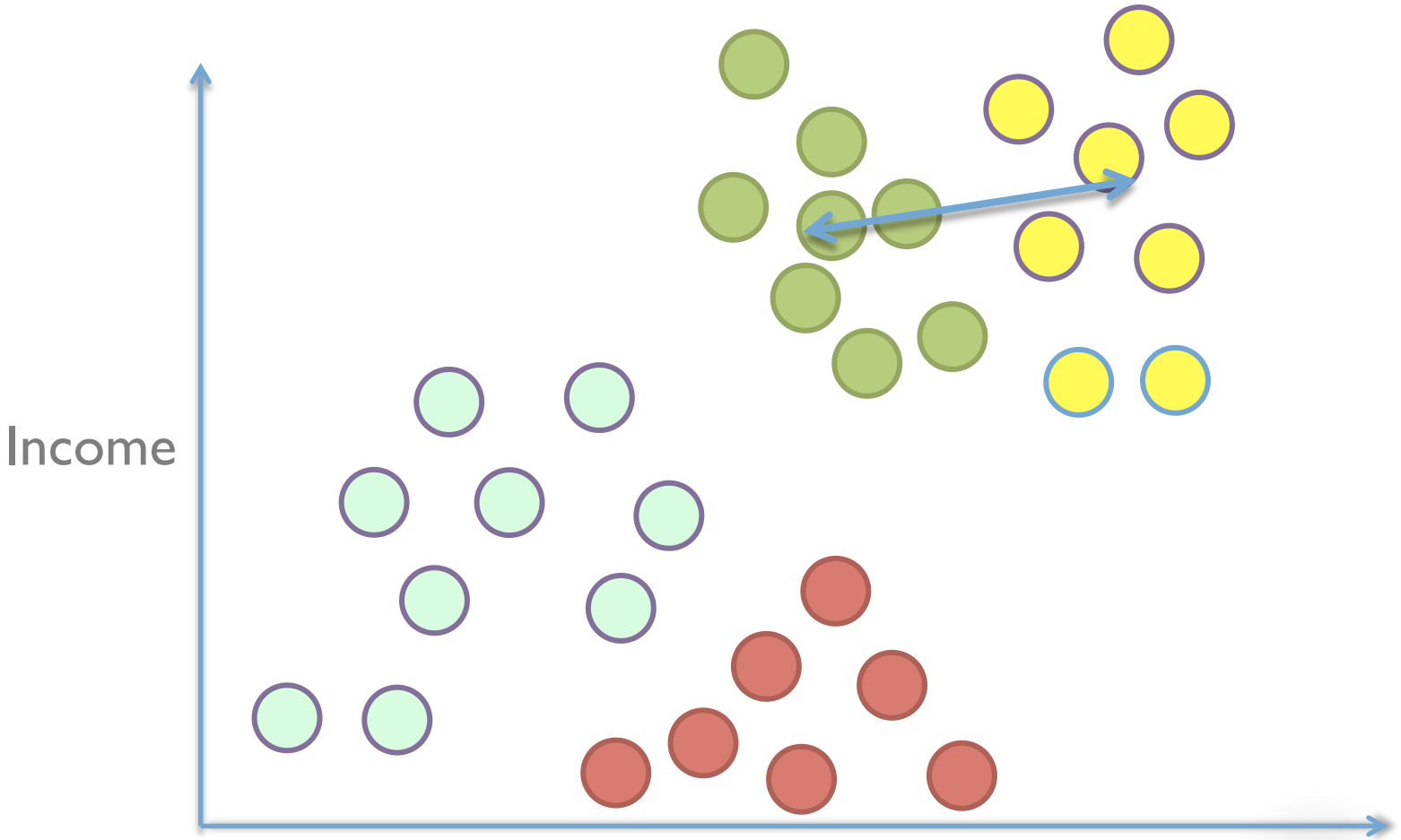
linkage = "average"

Distance between two cluster is average of all pairwise distance



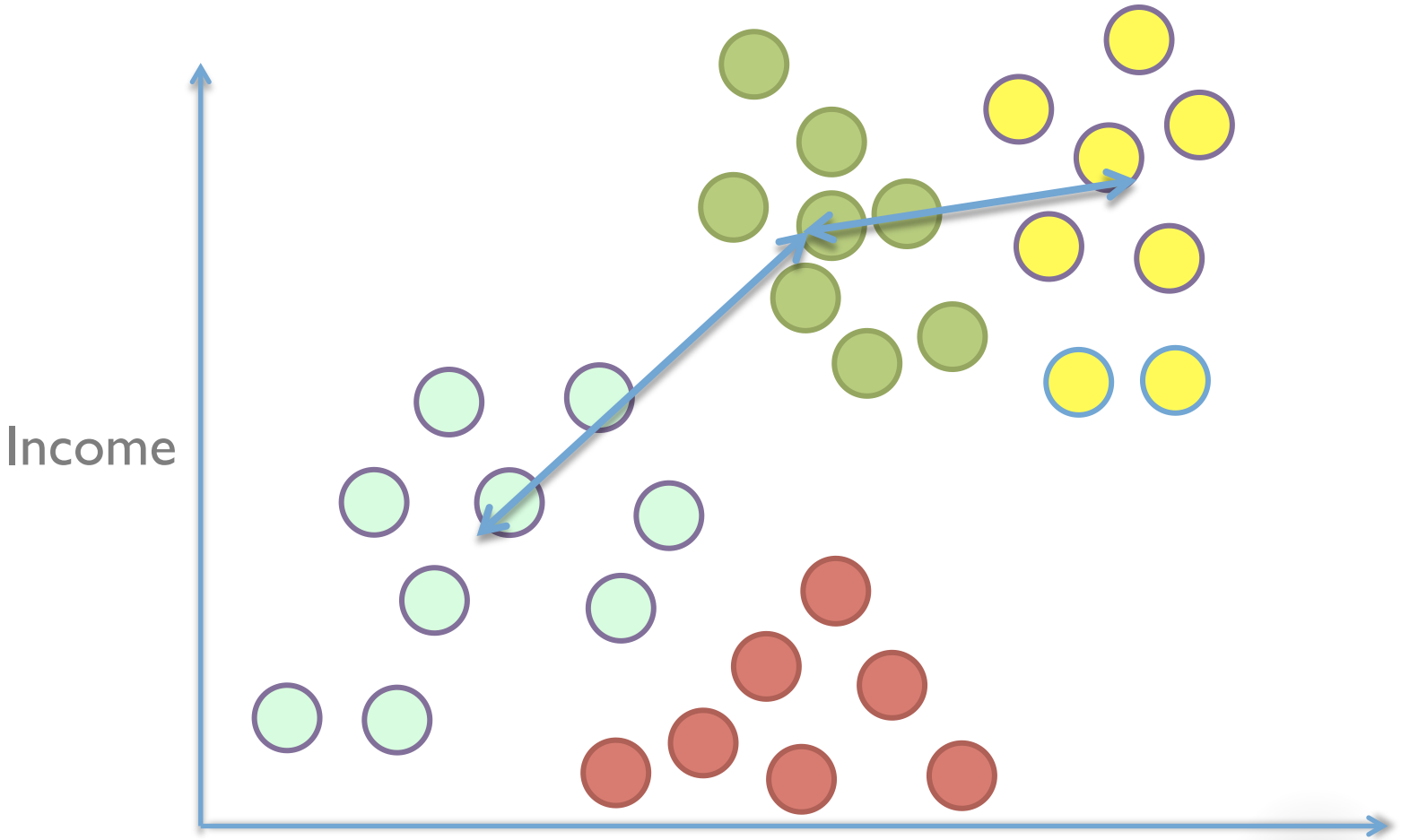
linkage = “average”

Distance between two cluster is average of all pairwise distance



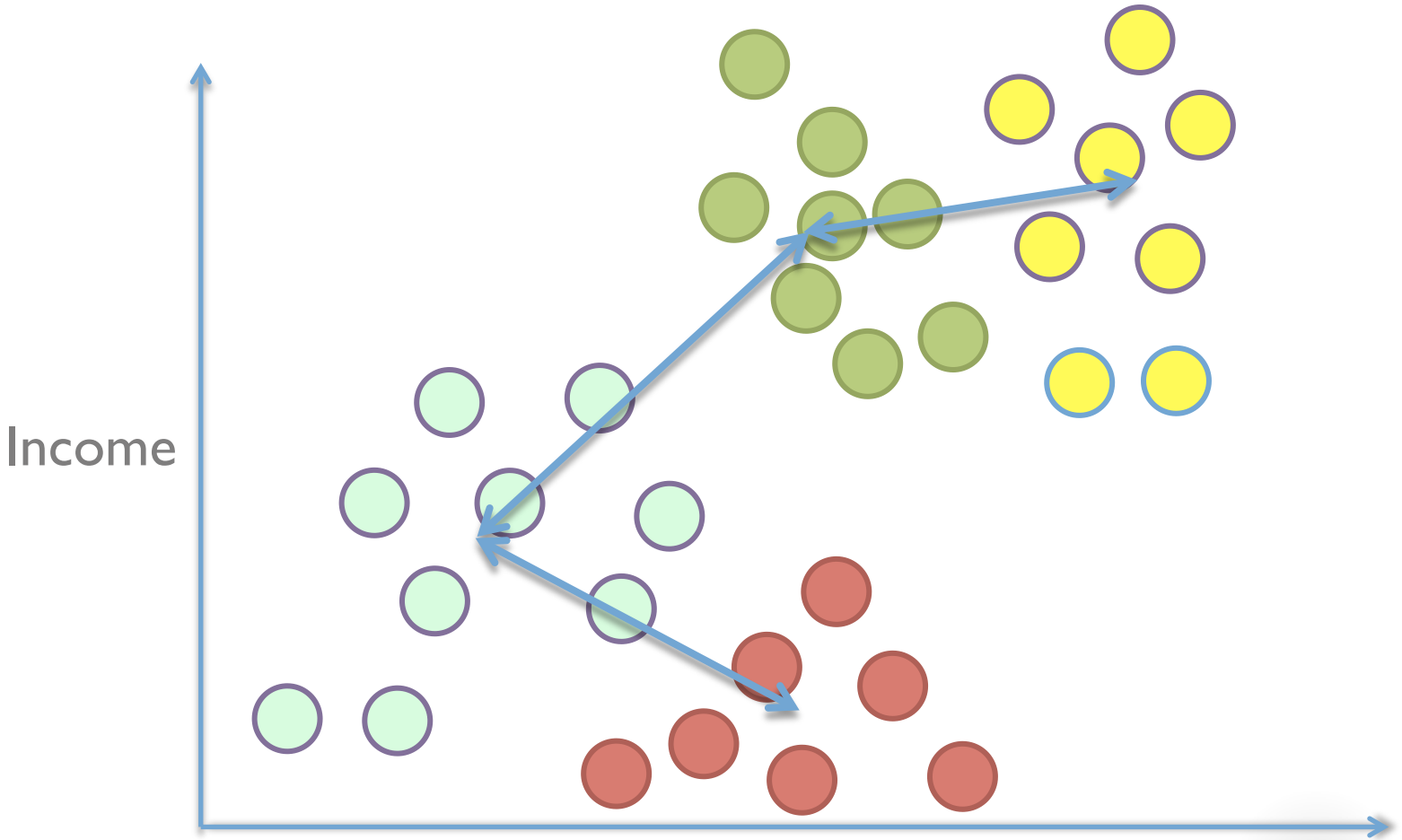
linkage = “average”

Distance between two cluster is average of all pairwise distance



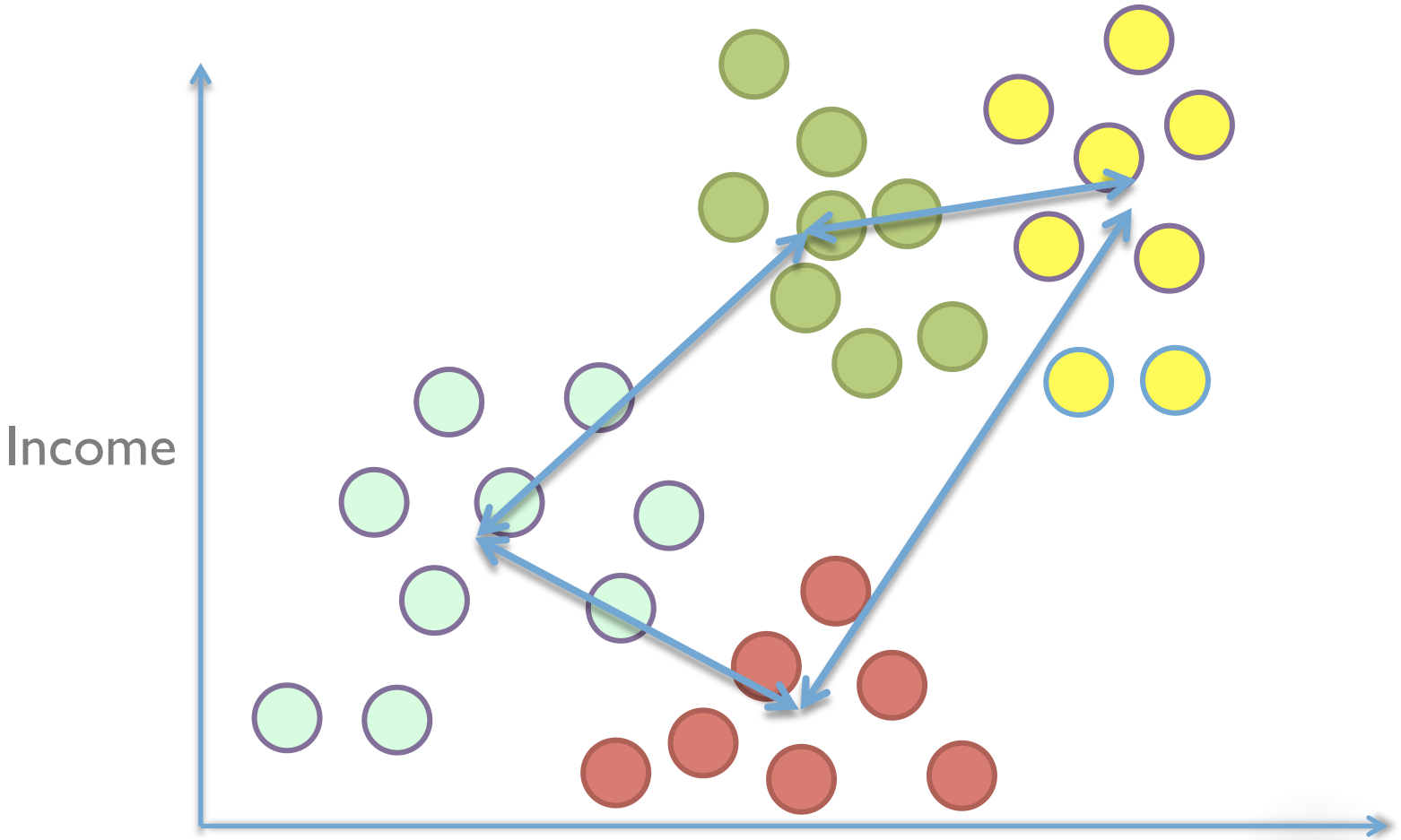
linkage = "average"

Distance between two cluster is average of all pairwise distance



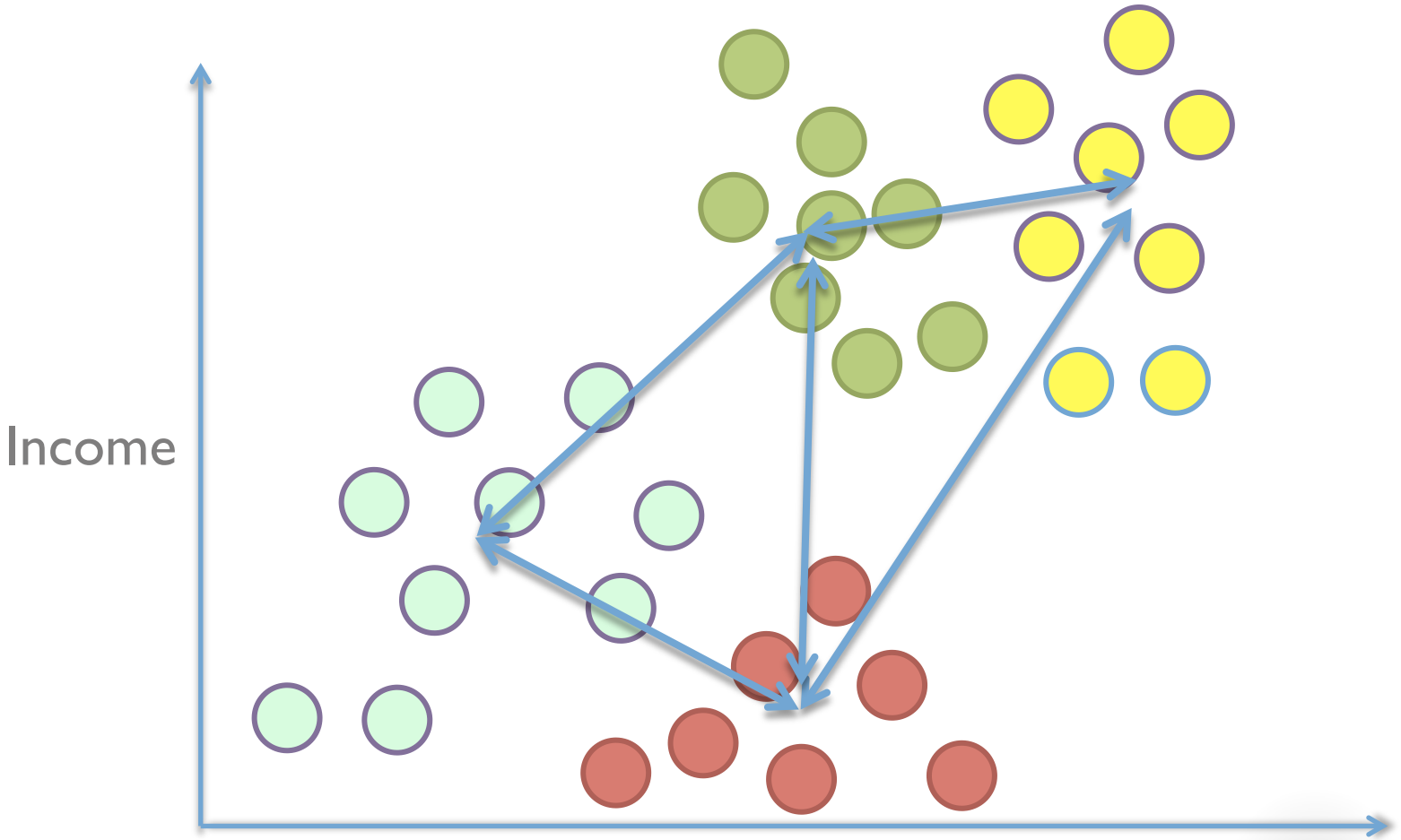
linkage = “average”

Distance between two cluster is average of all pairwise distance



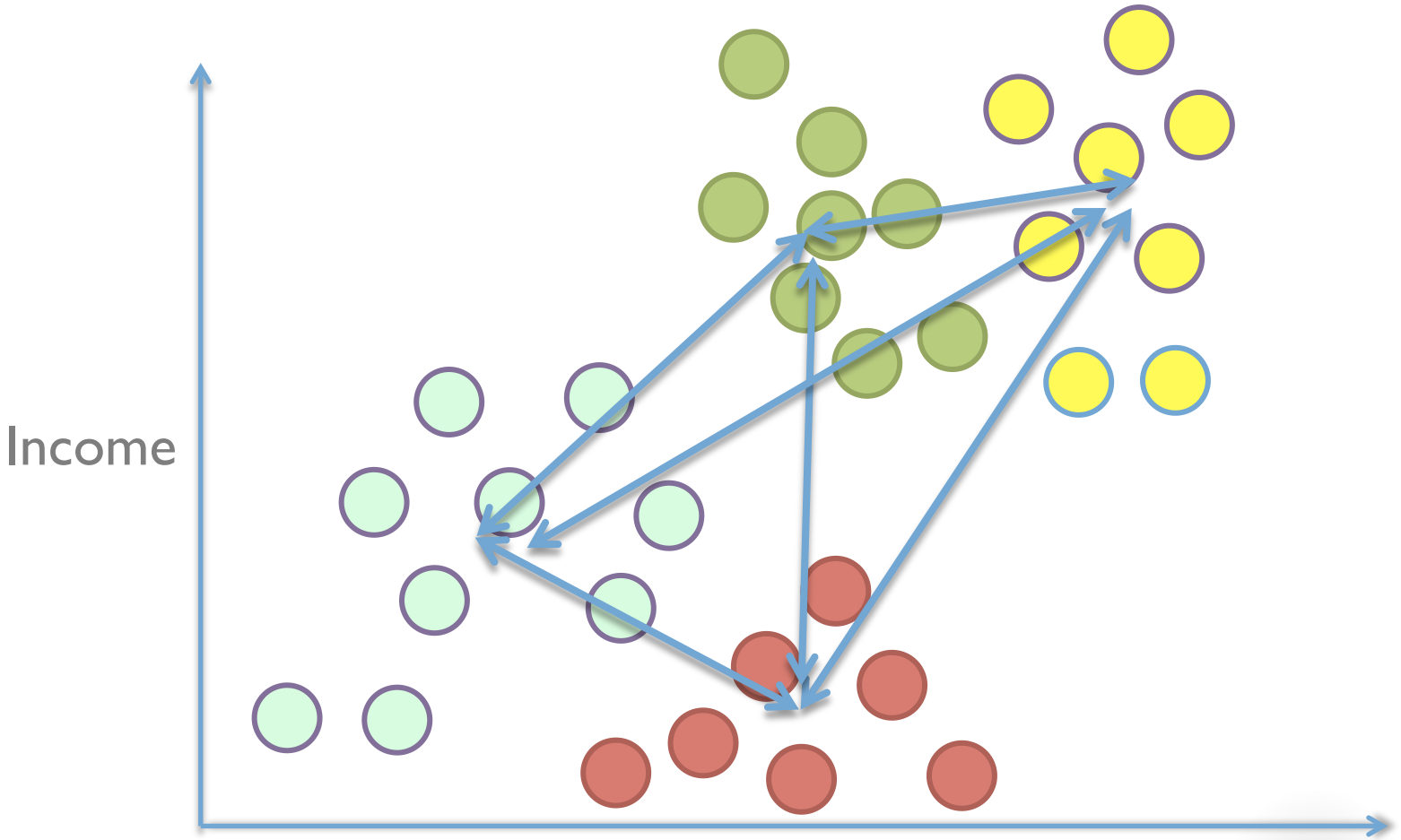
linkage = "average"

Distance between two cluster is average of all pairwise distance



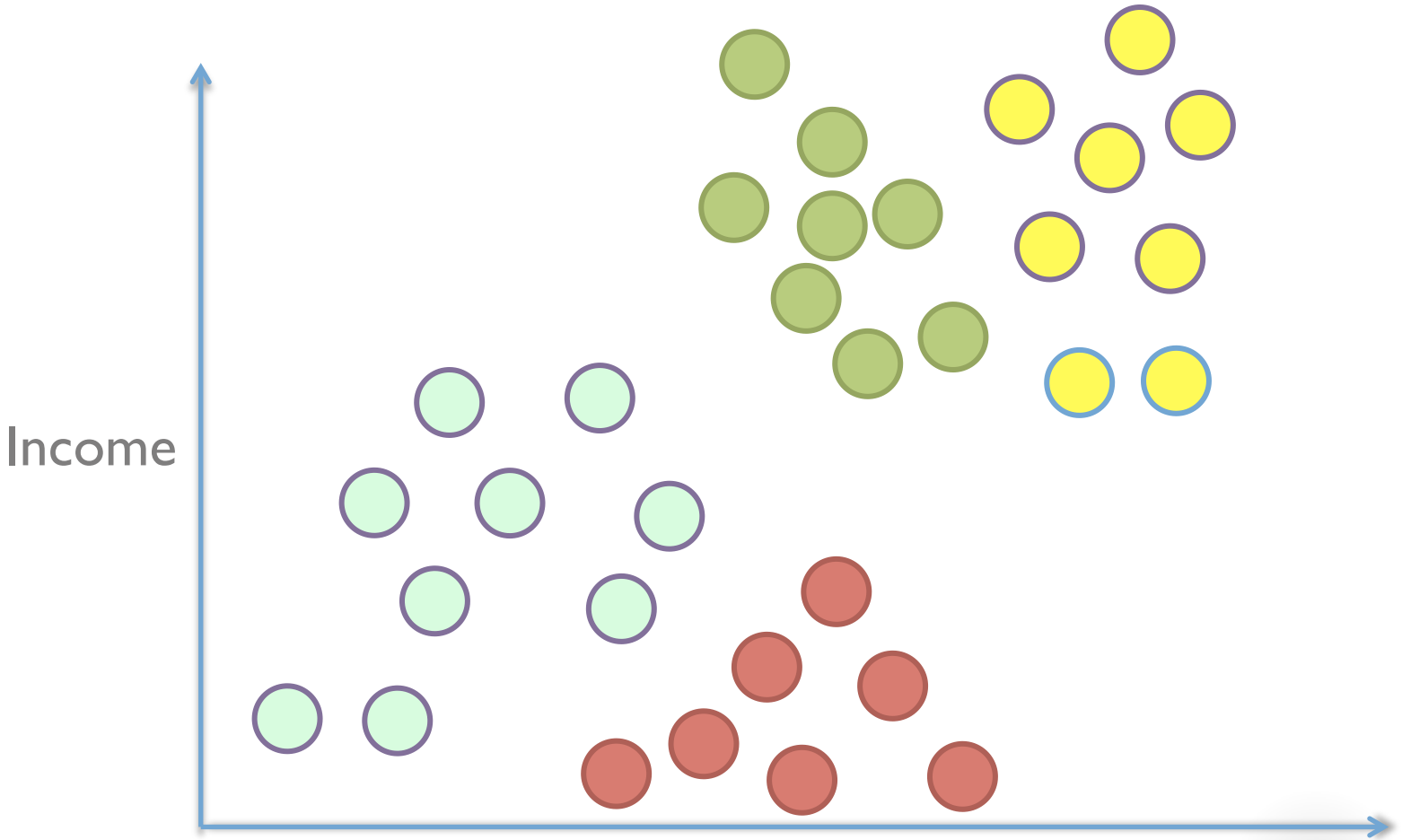
linkage = “average”

Slower. No chains. Not sensitive to outliers.



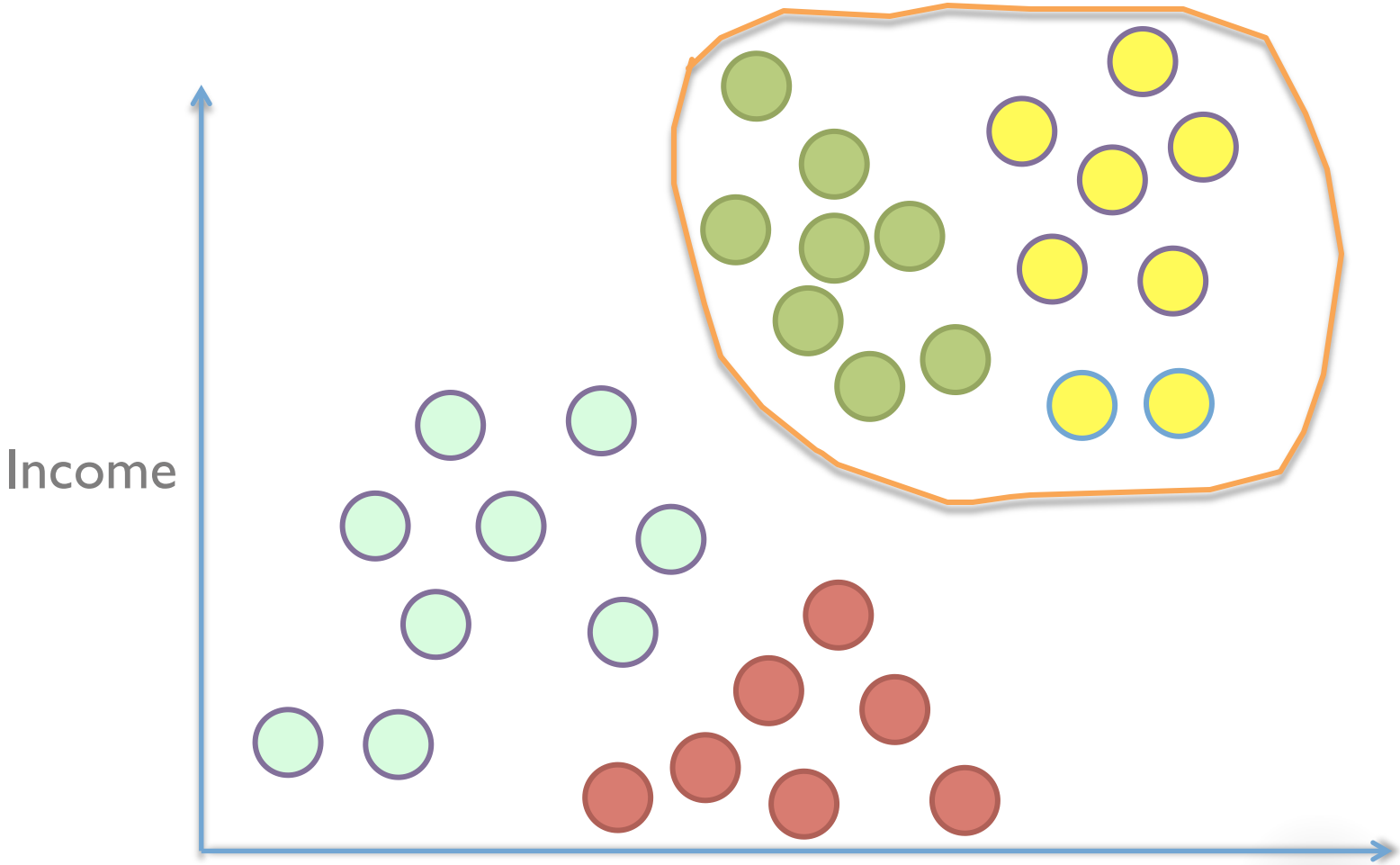
linkage = "ward"

Don't merge based on distance. Merge the two whose combination will give the best score (lowest inertia).



linkage = “ward”

This will choose the merge with the minimum within-cluster variance (high density clusters).



```
from sklearn.cluster import AgglomerativeClustering
Agglomerative Clustering(linkage="Ward").fit_predict(X)
```

or

```
from sklearn.cluster import Ward
Ward().fit_predict(X)
```

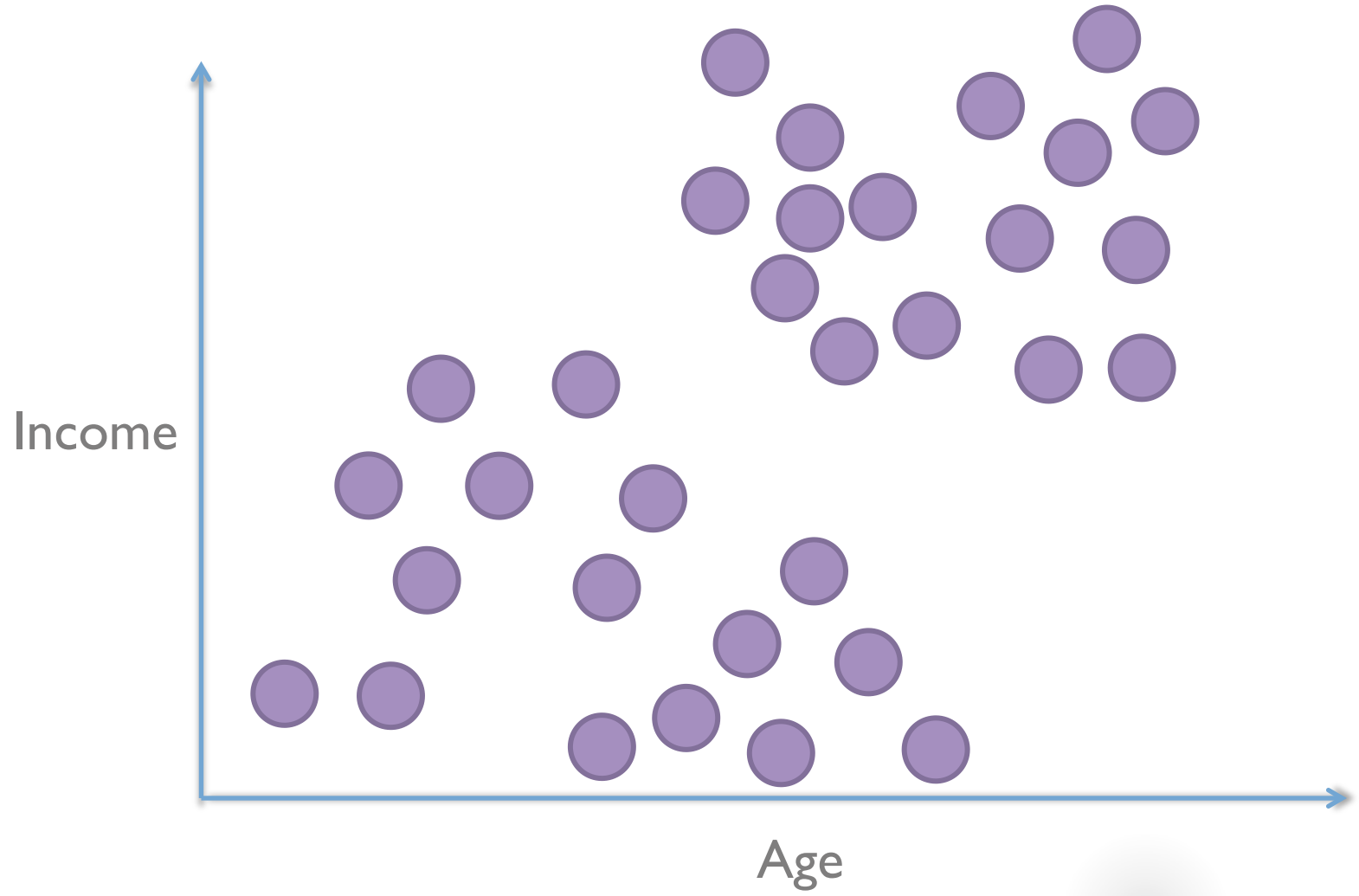
(Same thing)

```
from sklearn.cluster import AgglomerativeClustering

AgglomerativeClustering(….,
                        ….
                         ,
                        linkage = “ward”,
                        ….
                         ,
                        affinity = “euclidian”,
                        ….
                         )
```

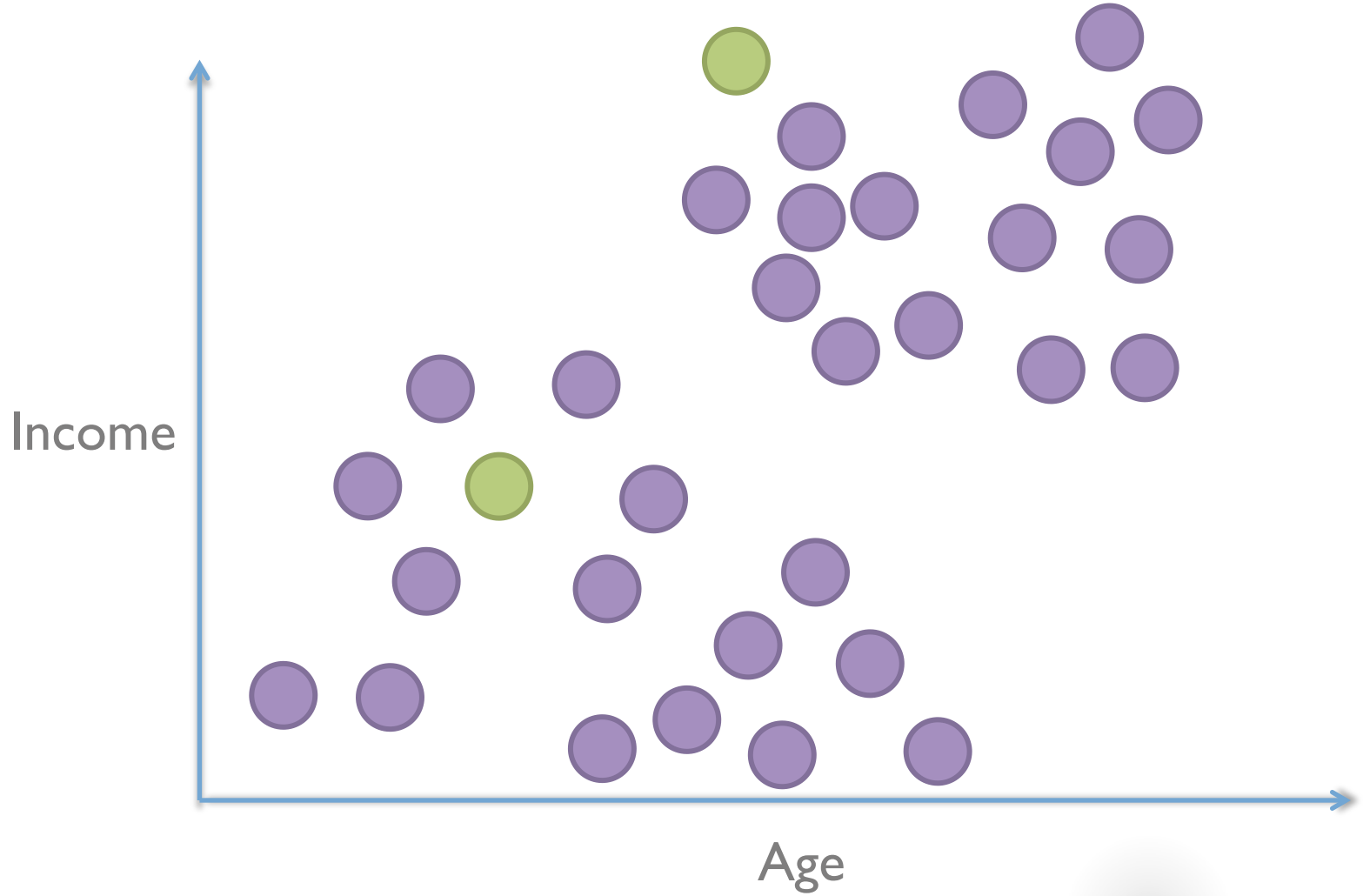
```
from sklearn.cluster import AgglomerativeClustering

AgglomerativeClustering(….,
                        ….
                         ,
                        linkage = “ward”,
                        ….
                         ,
                        affinity = “euclidian”,
                        ….
                         )
```

Distance Metrics

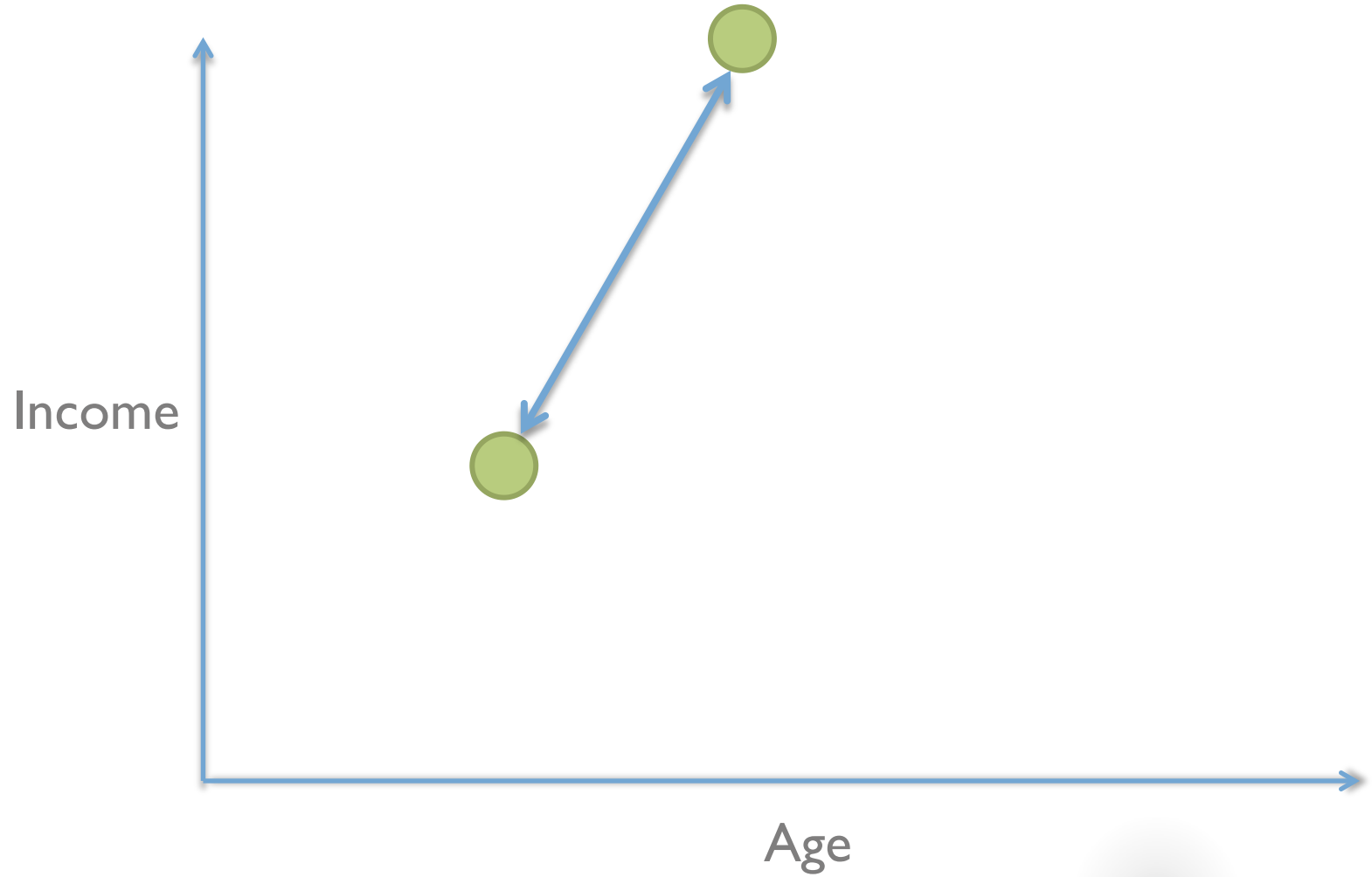
Euclidean Distance



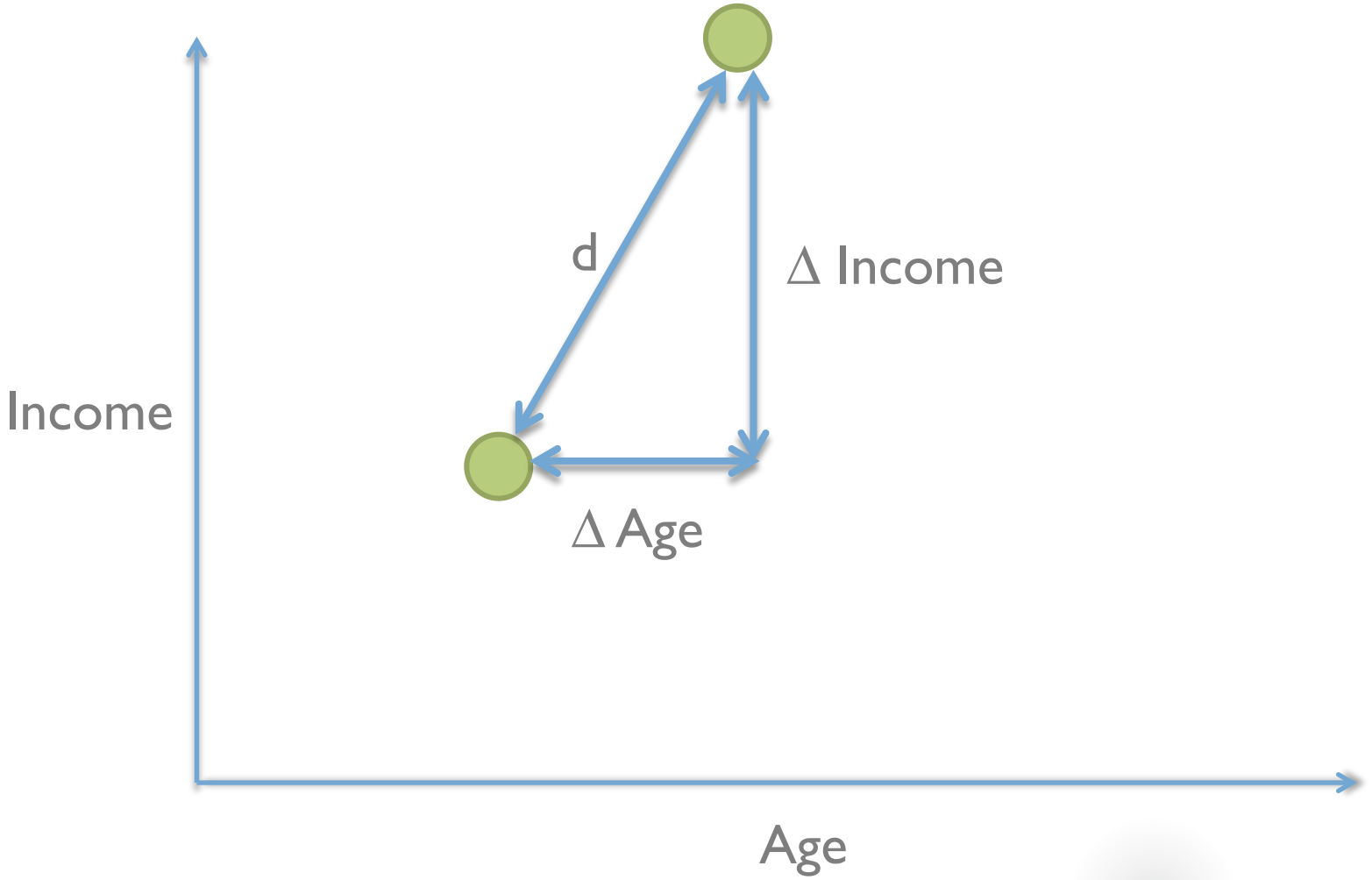
Euclidean Distance



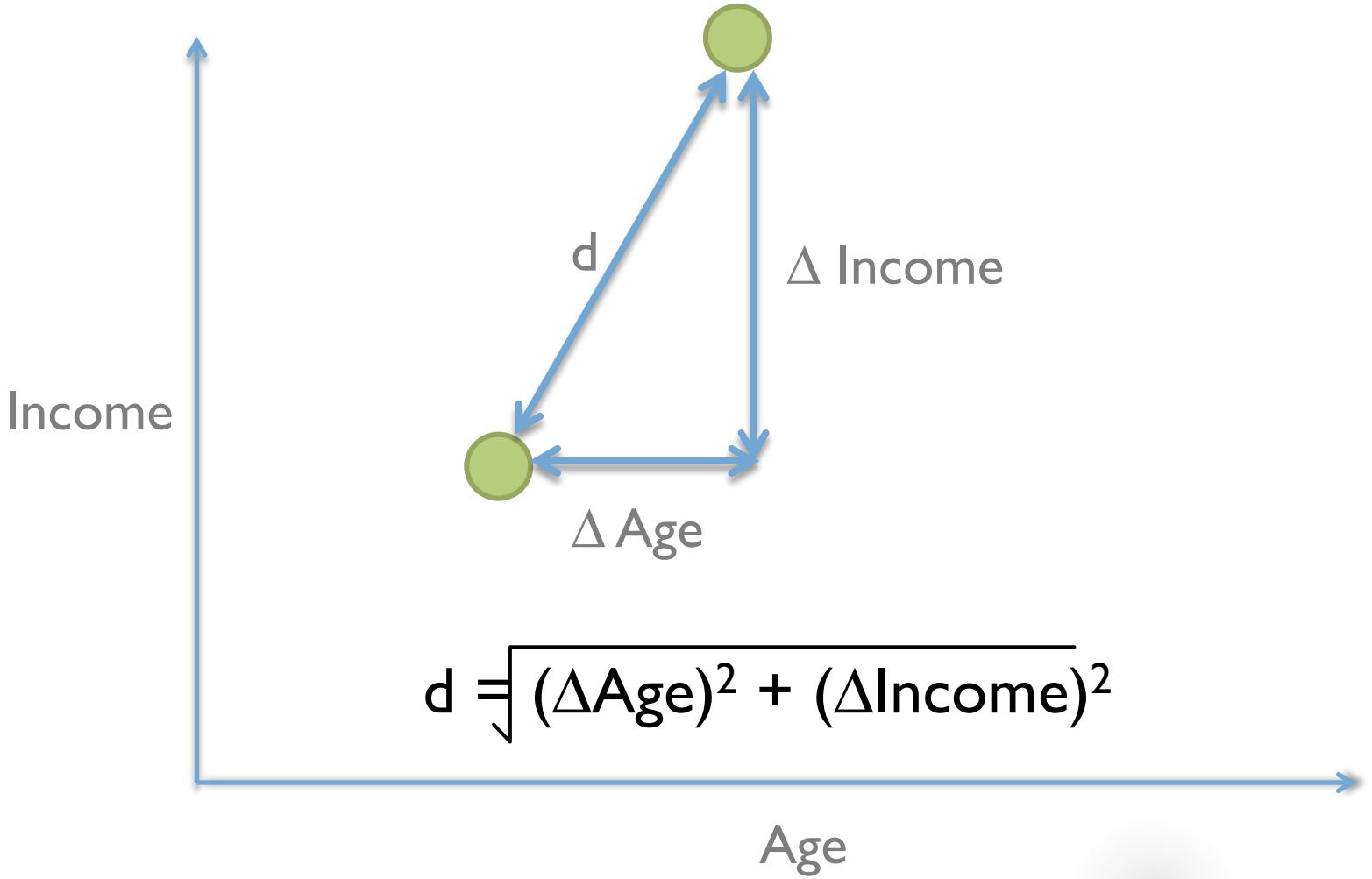
Euclidean Distance



Euclidean Distance

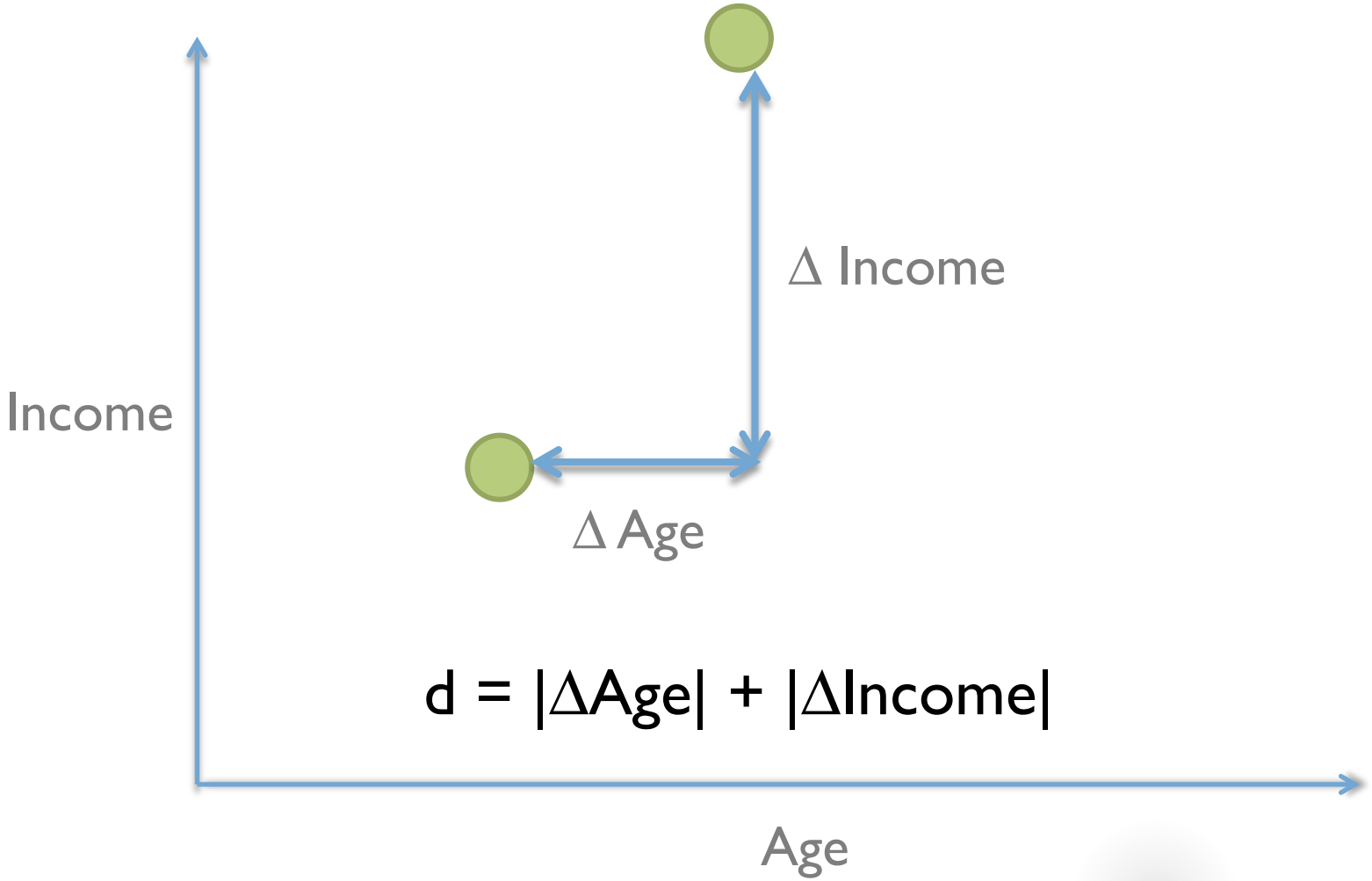


Euclidean Distance (L2 dist)



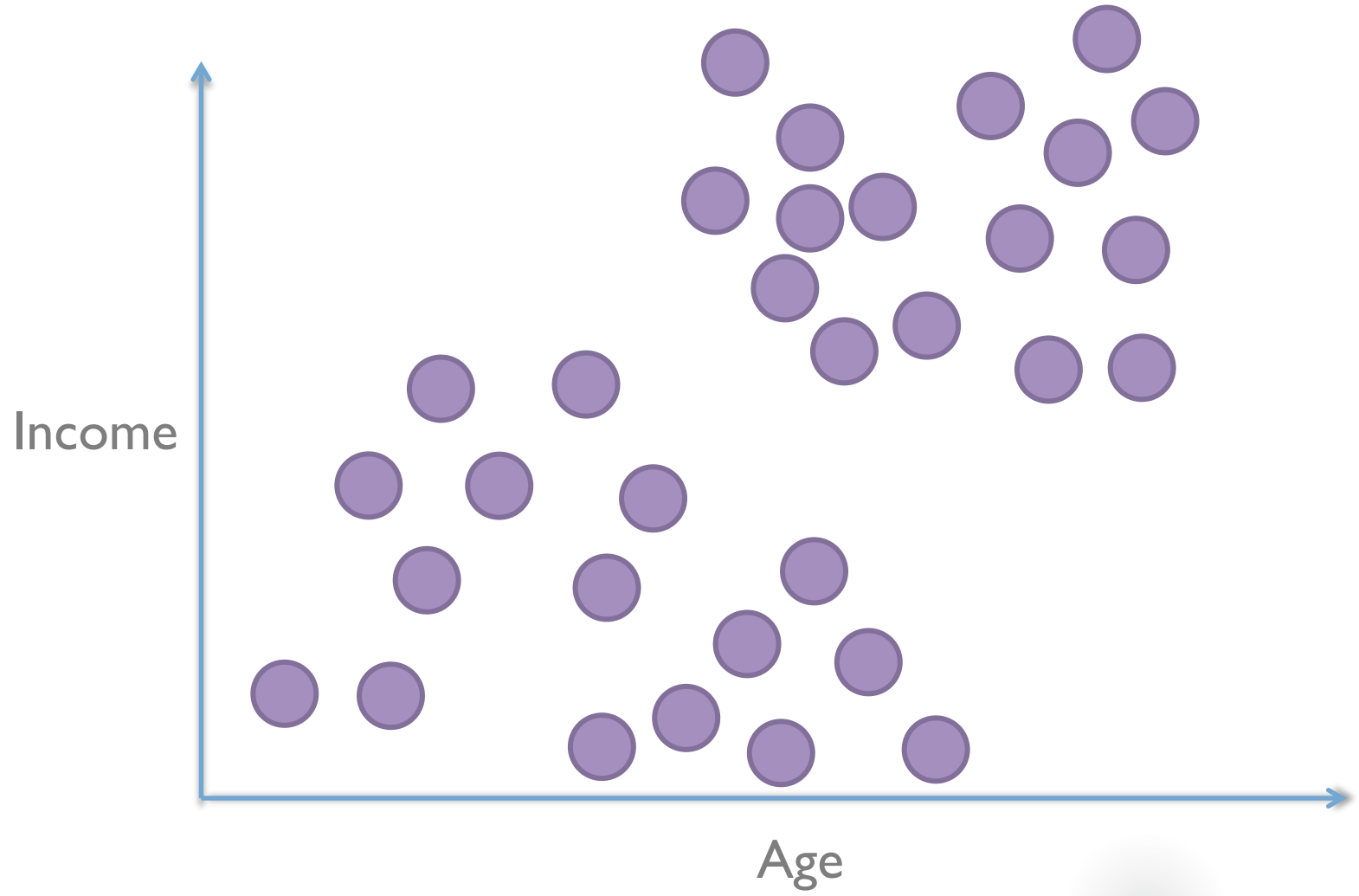
$$d = \sqrt{(\Delta Age)^2 + (\Delta Income)^2}$$

Manhattan Distance (Cityblock dist, L1 dist)

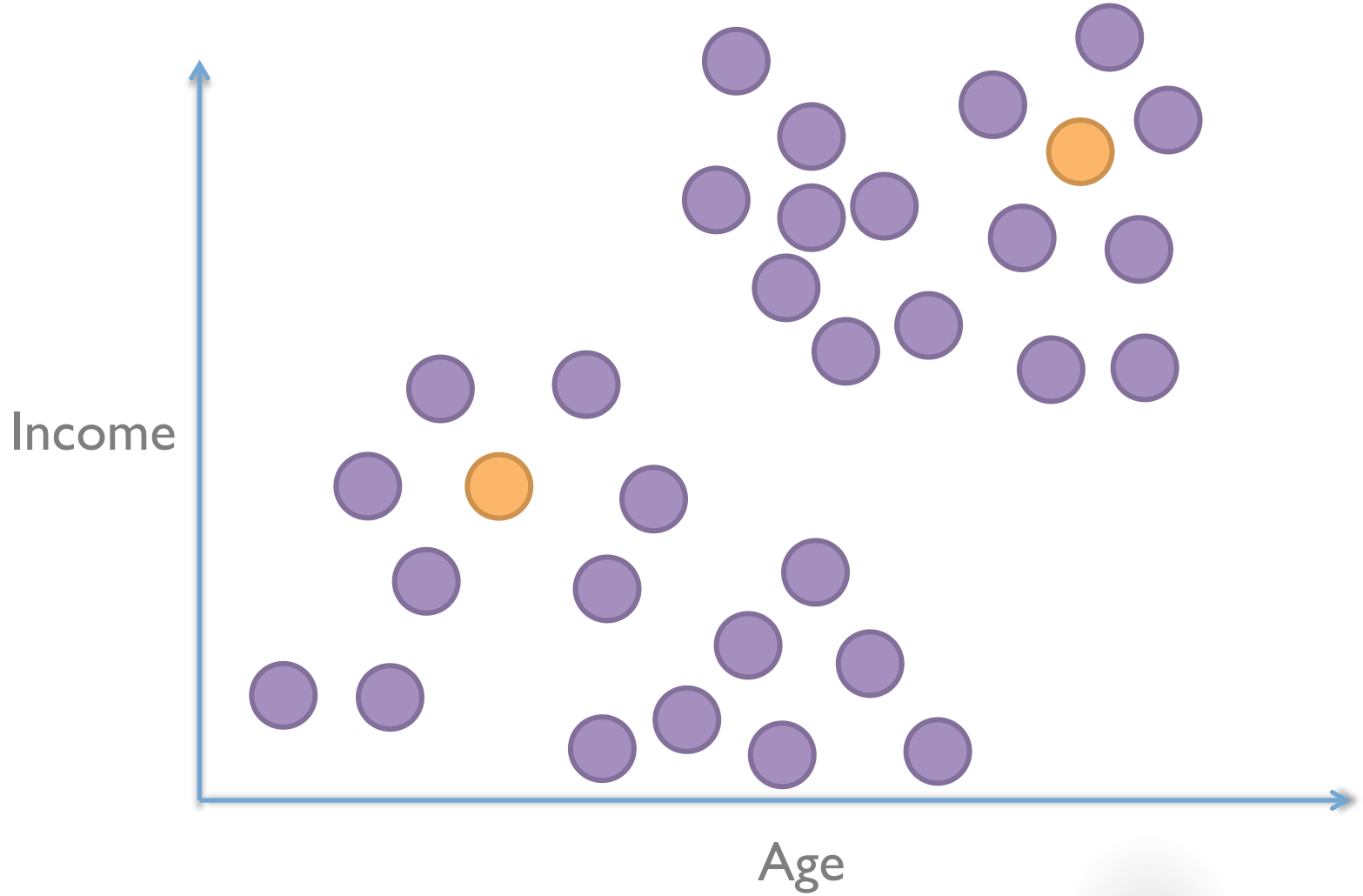


$$d = |\Delta Age| + |\Delta Income|$$

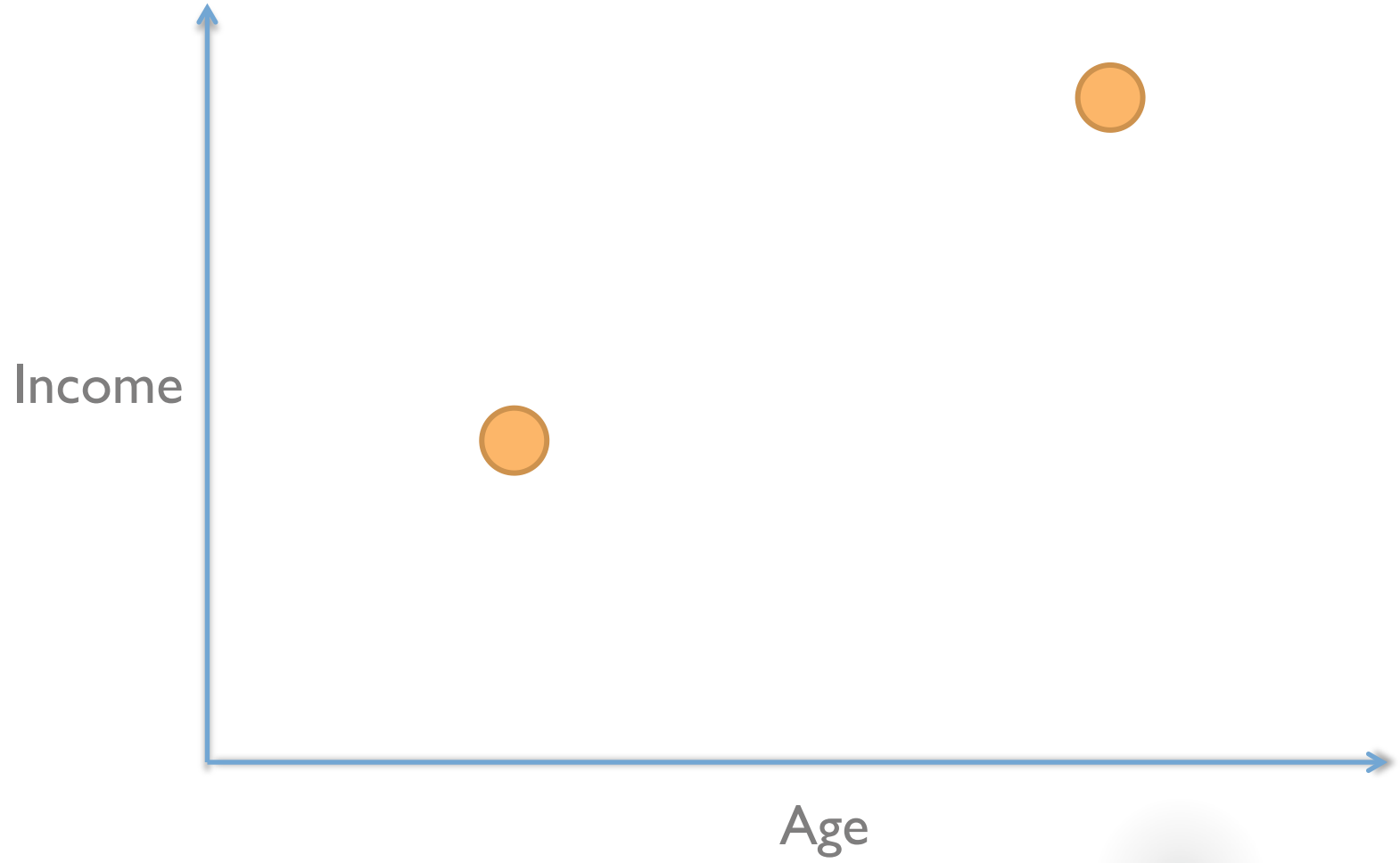
Cosine Distance



Cosine Distance



Cosine Distance



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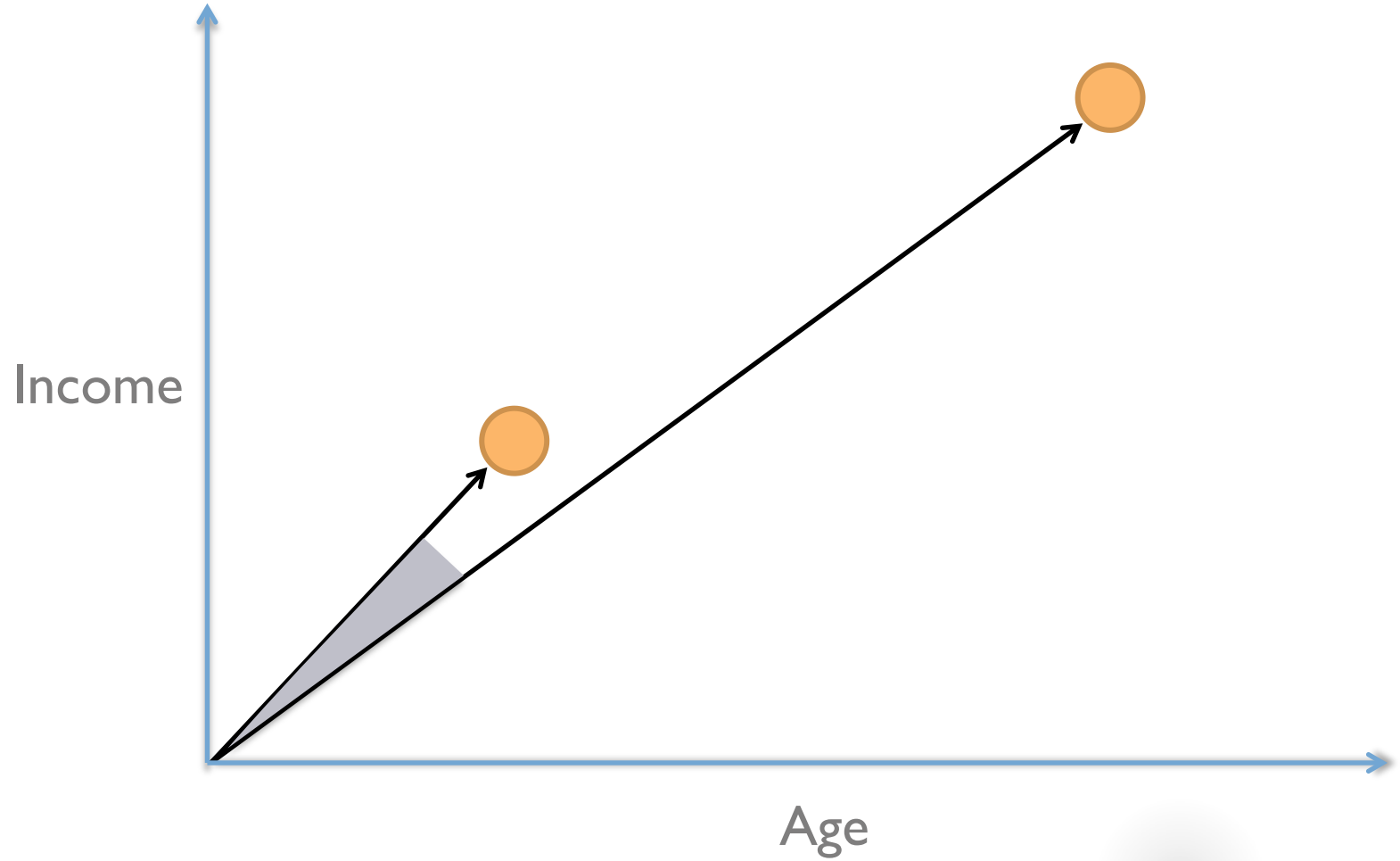
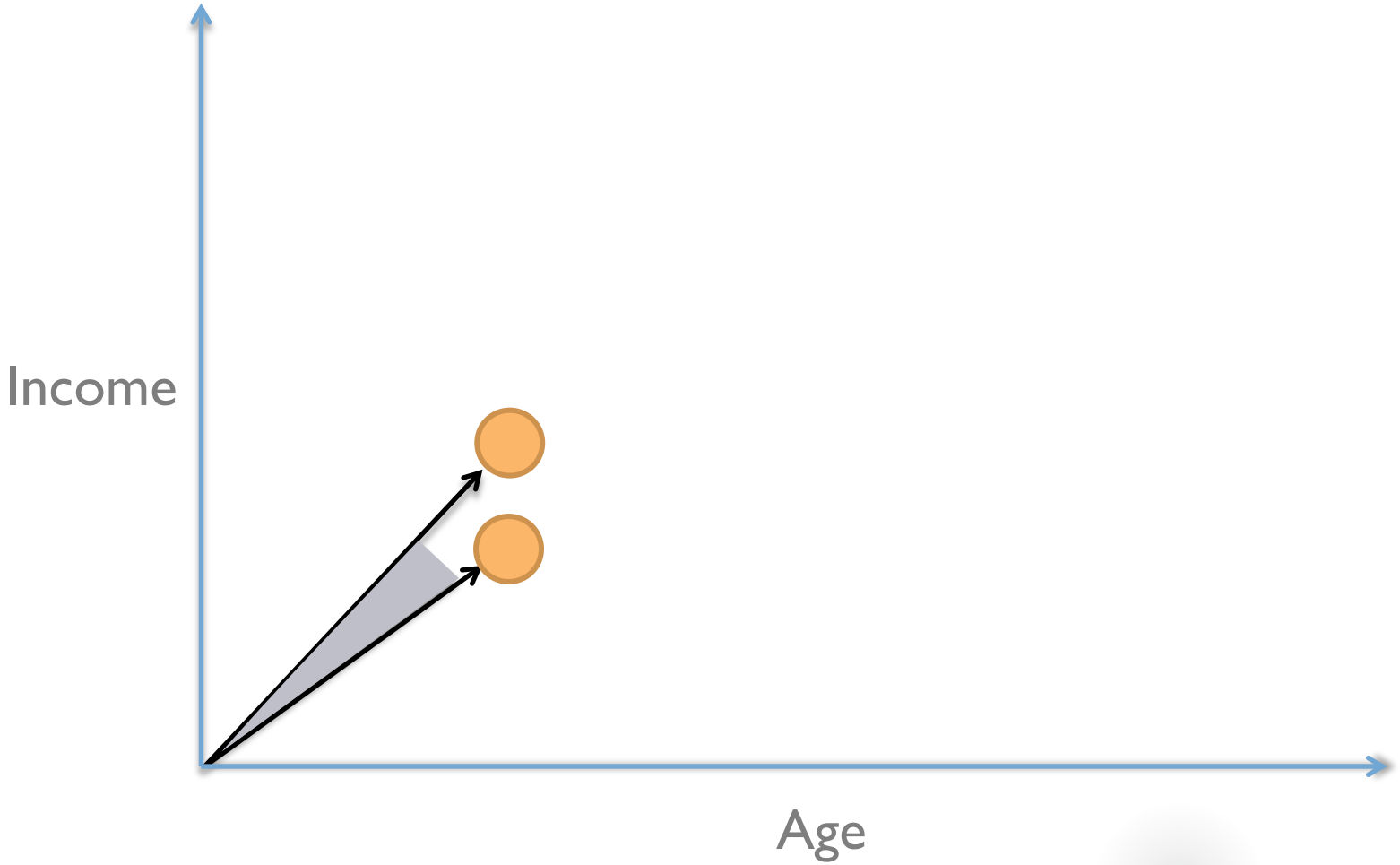
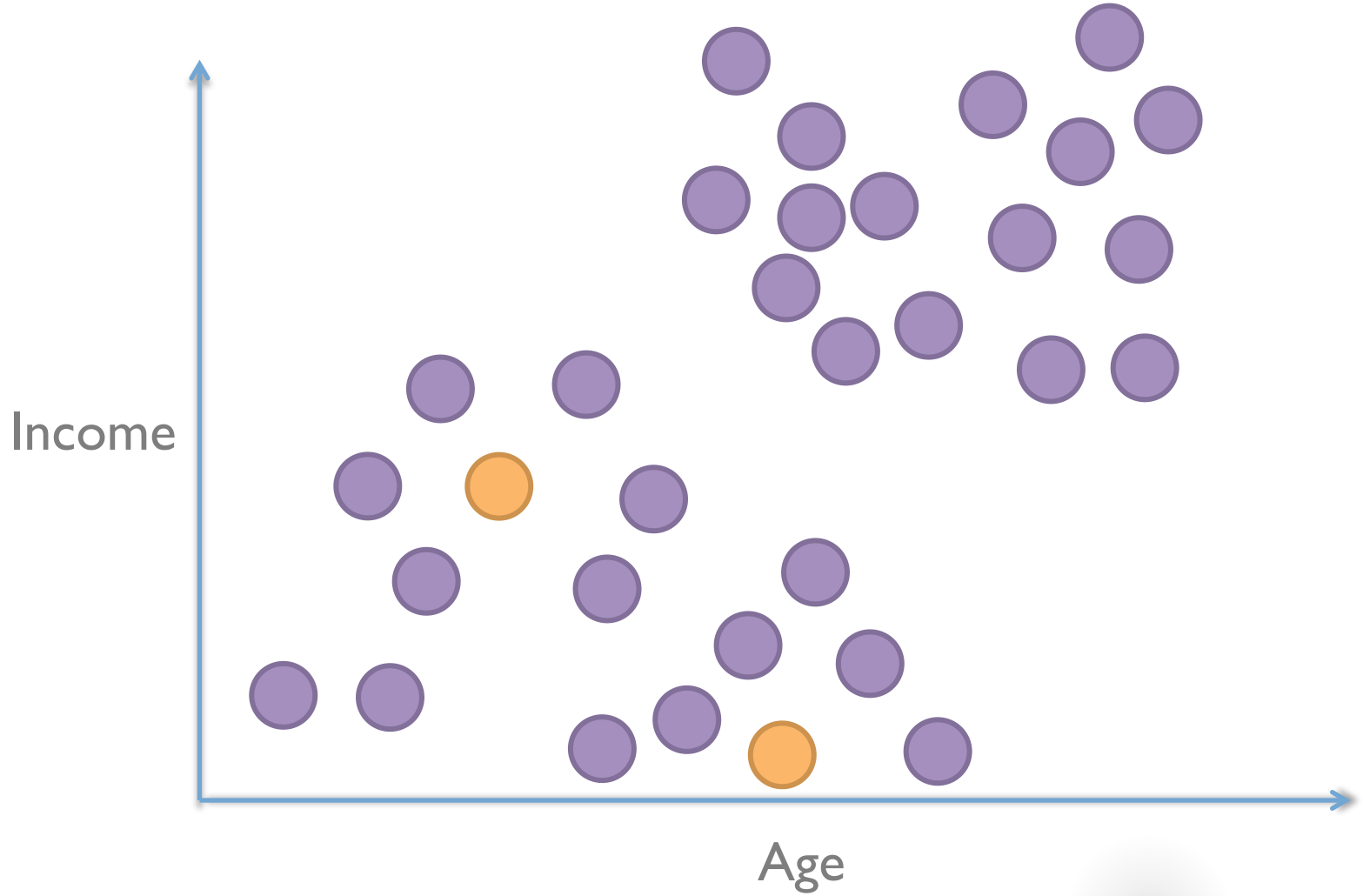


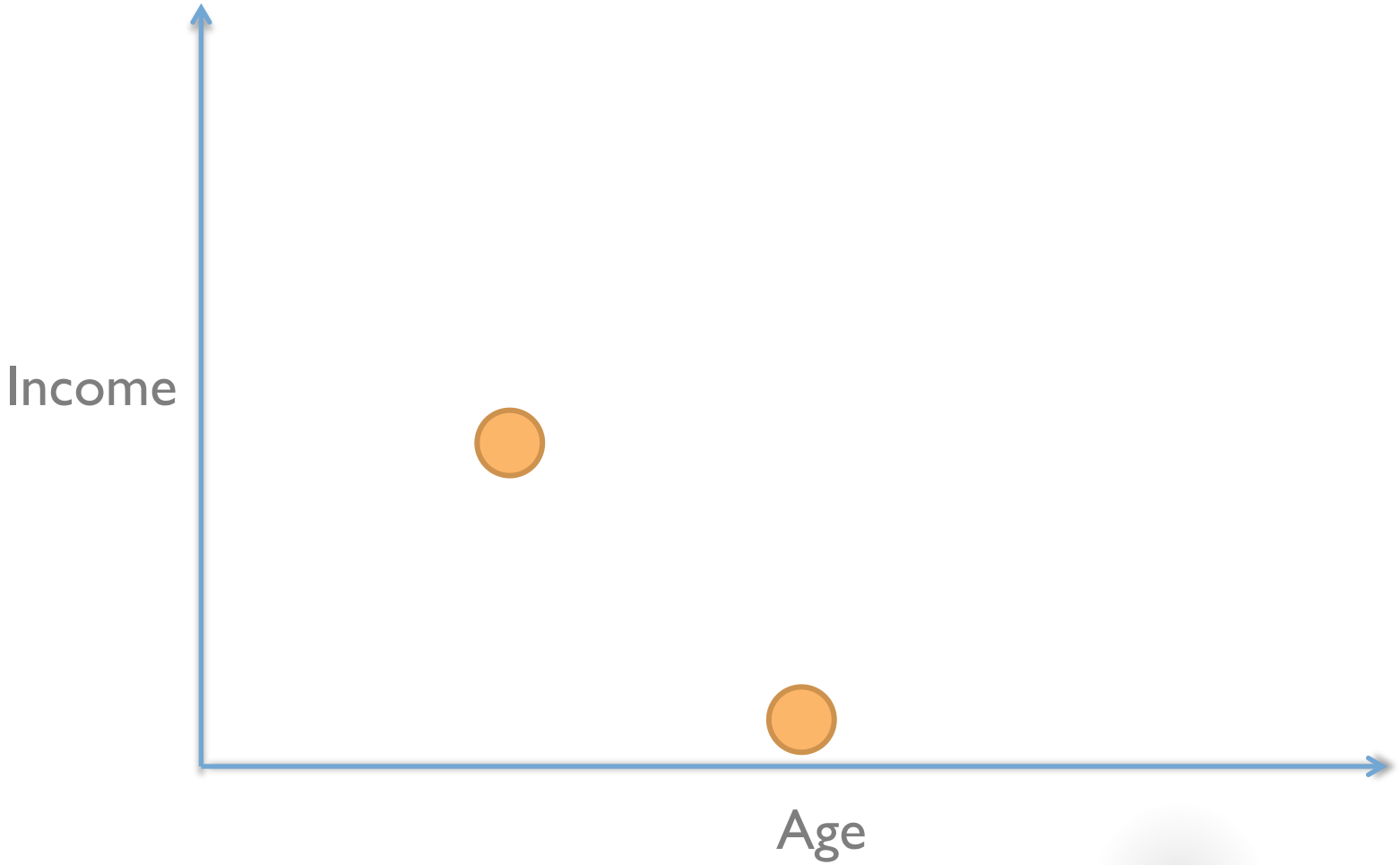
Cosine Distance



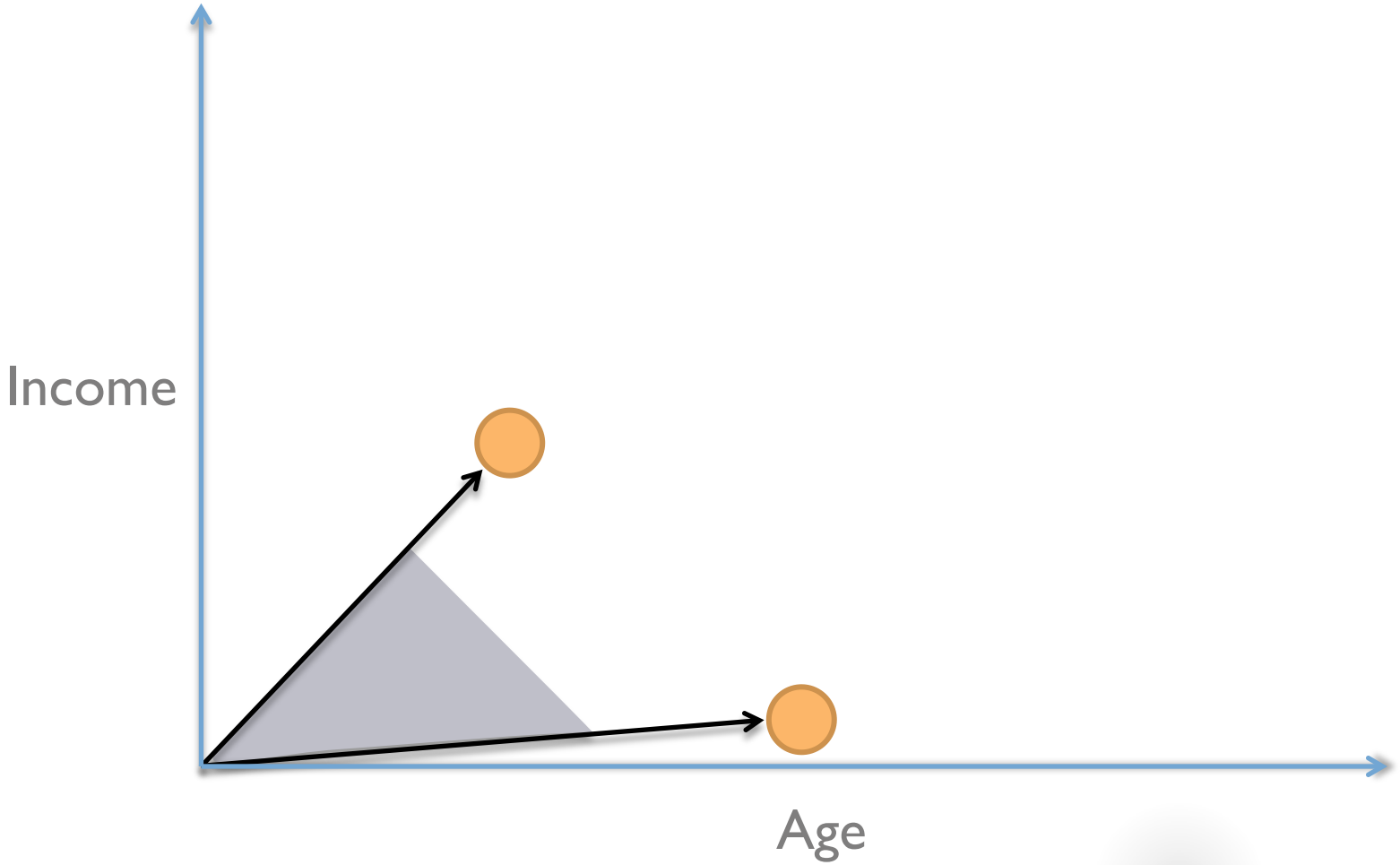
Cosine Distance



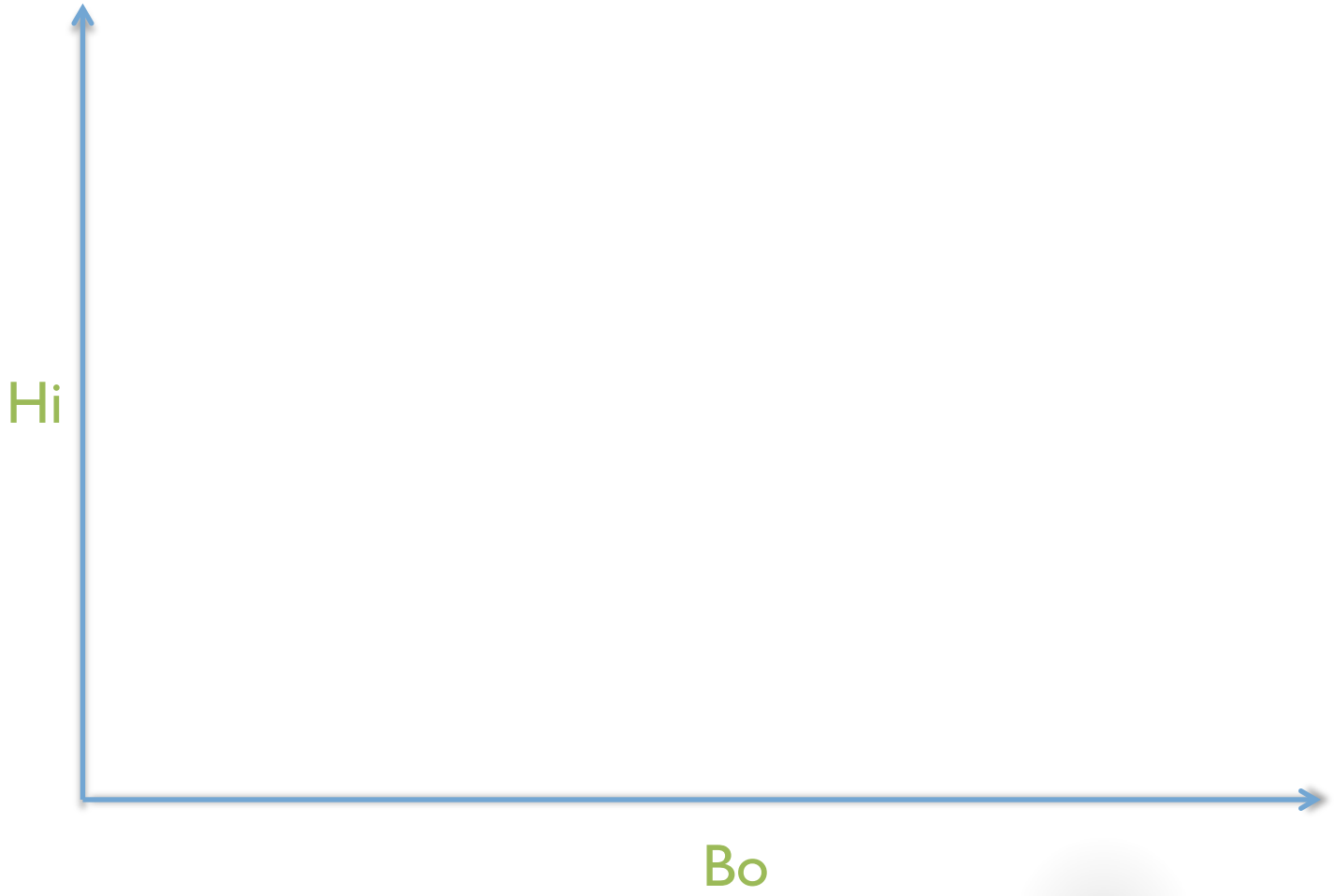
Cosine Distance



Cosine Distance



Cosine Distance is better for text data
Euclidean Distance is sensitive to doc. length



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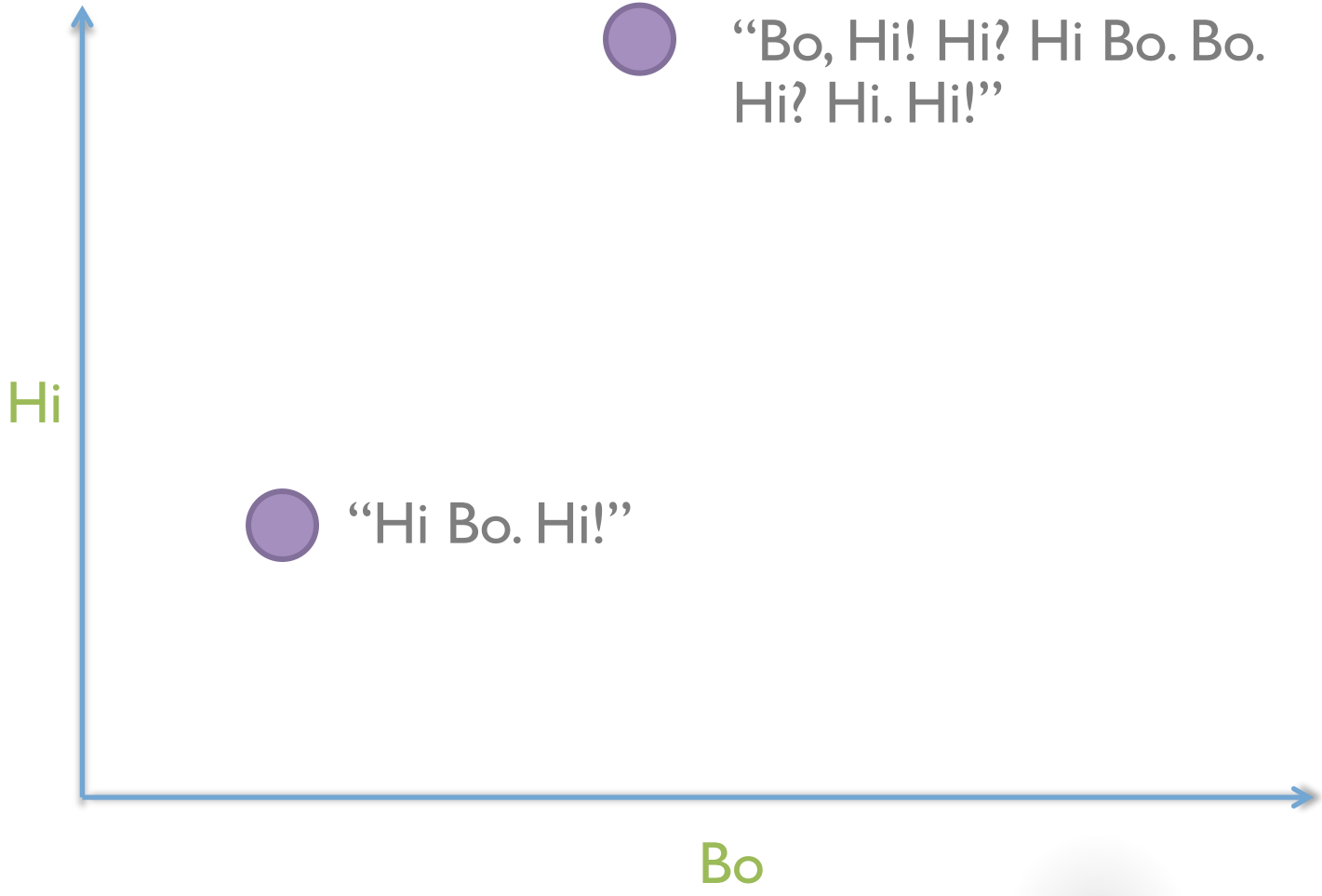

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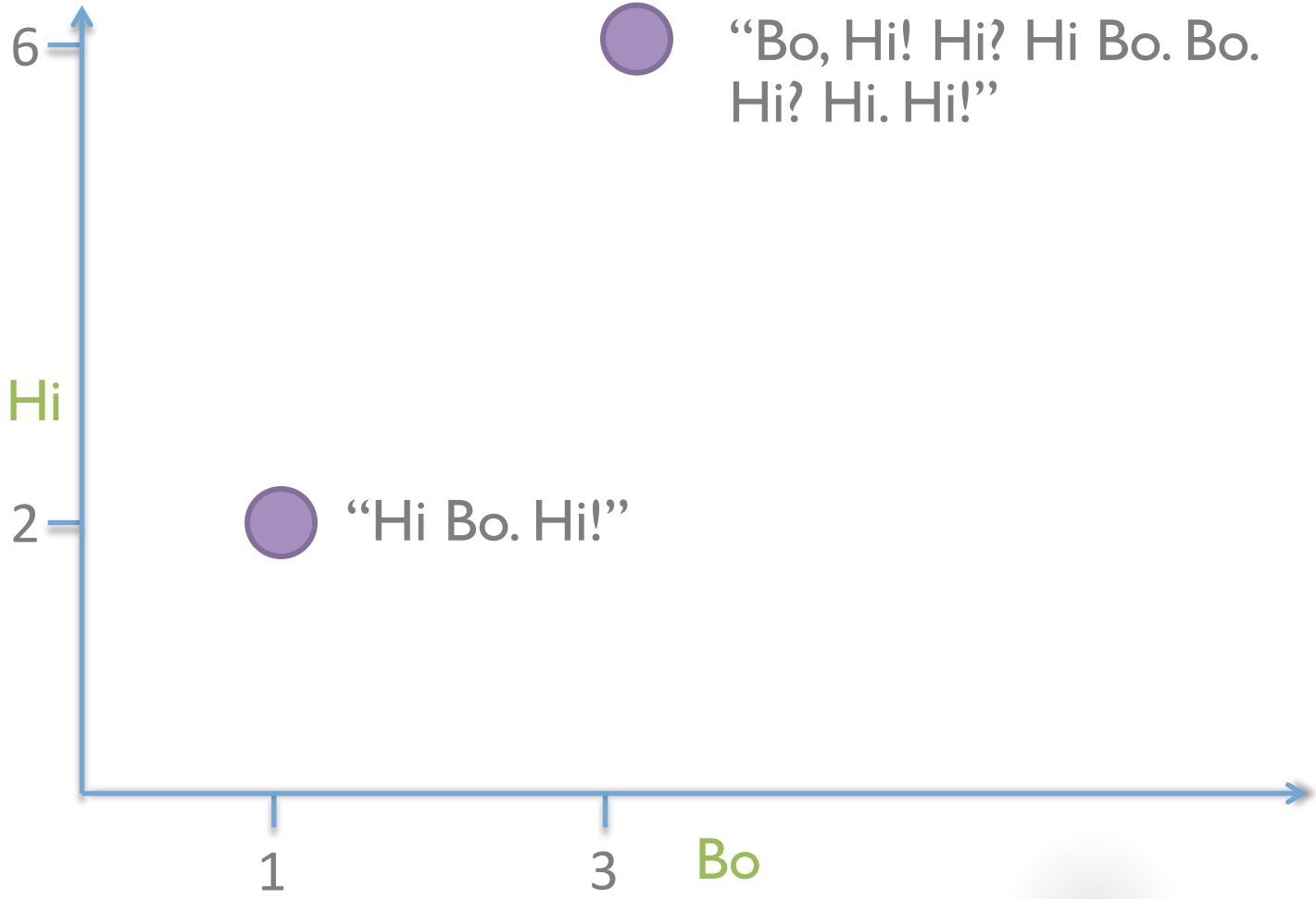

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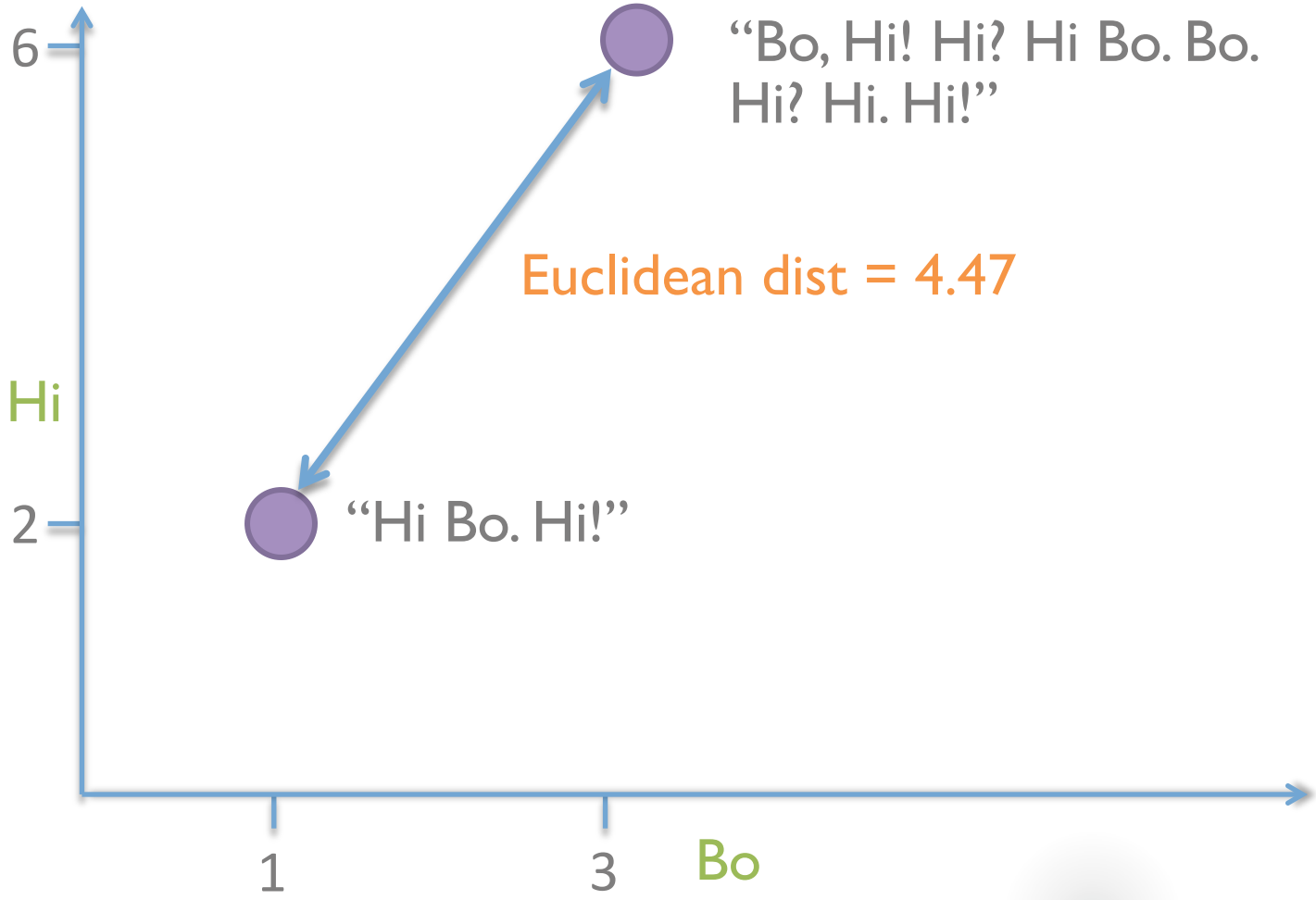

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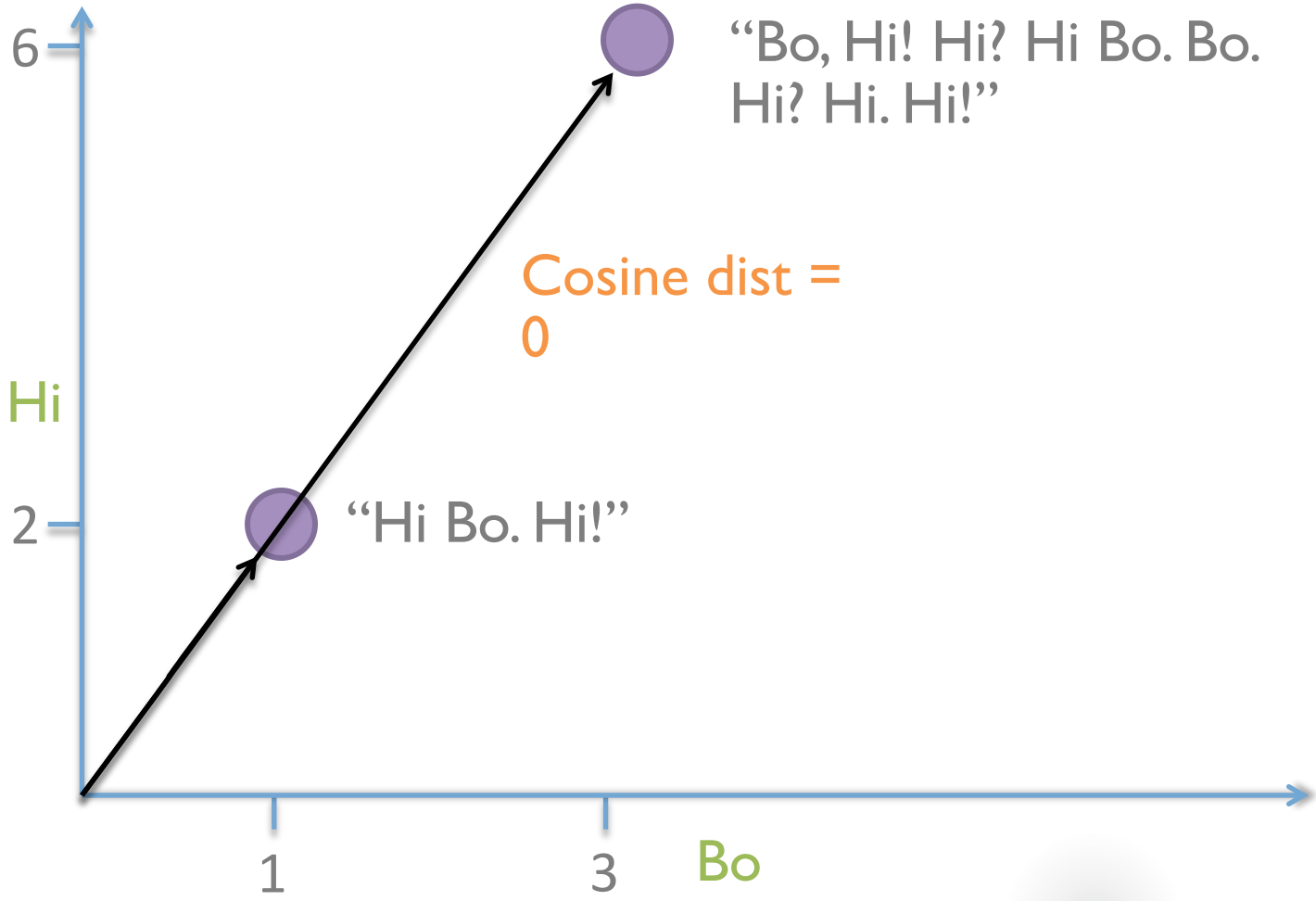
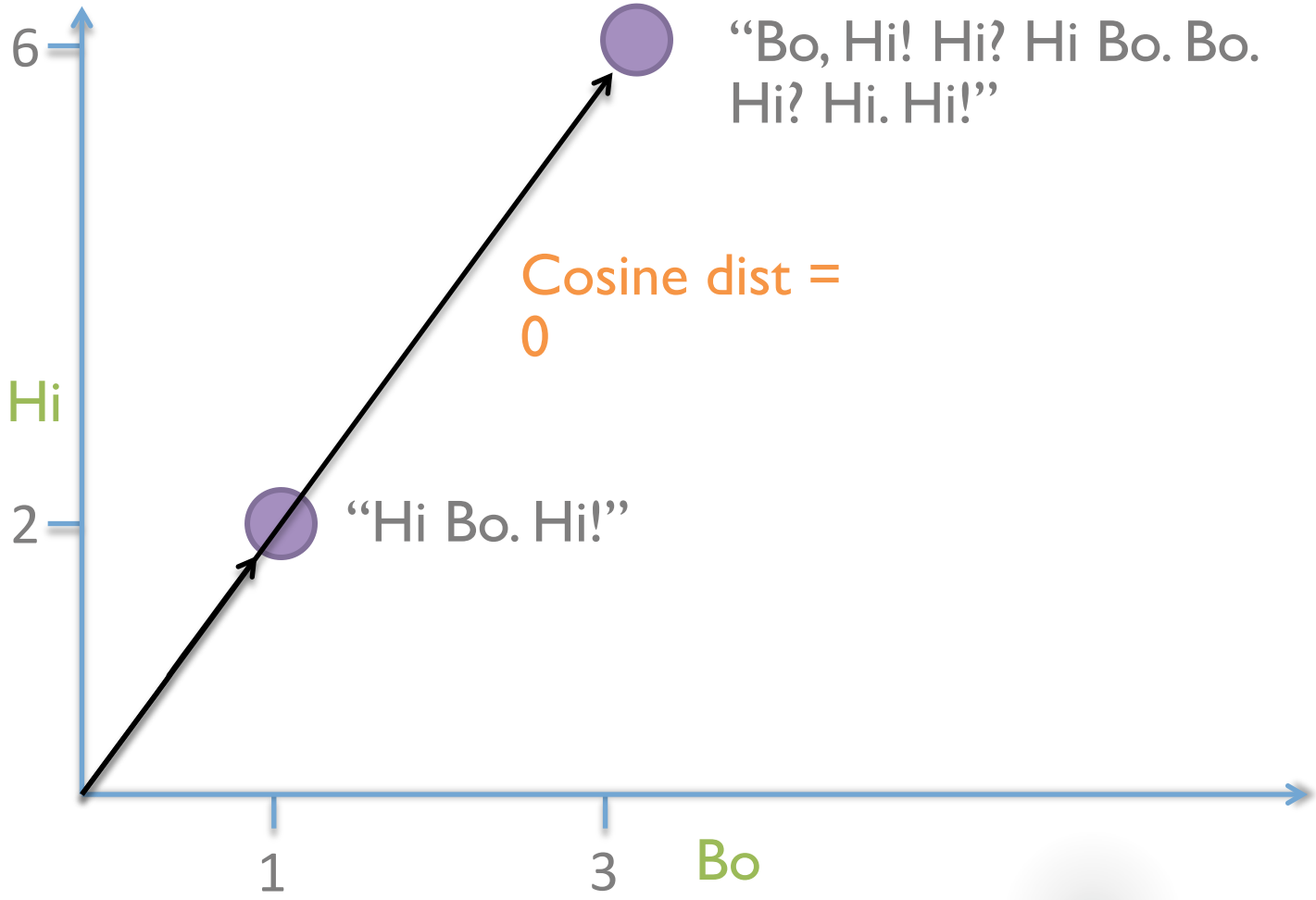


Cosine Distance captures the "meaning" distance better in a bag of words system



Jaccard Distance

Applies to sets (like bag of words)

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Sentence A: "I like chocolate ice cream."
set A = {I, like, chocolate, ice, cream}

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Jaccard dist

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Jaccard dist

$$1 - \frac{len(\{I, chocolate, cream\})}{len(\{I, like, chocolate, ice, cream, do, want, or, vanilla\})}$$

Jaccard Distance

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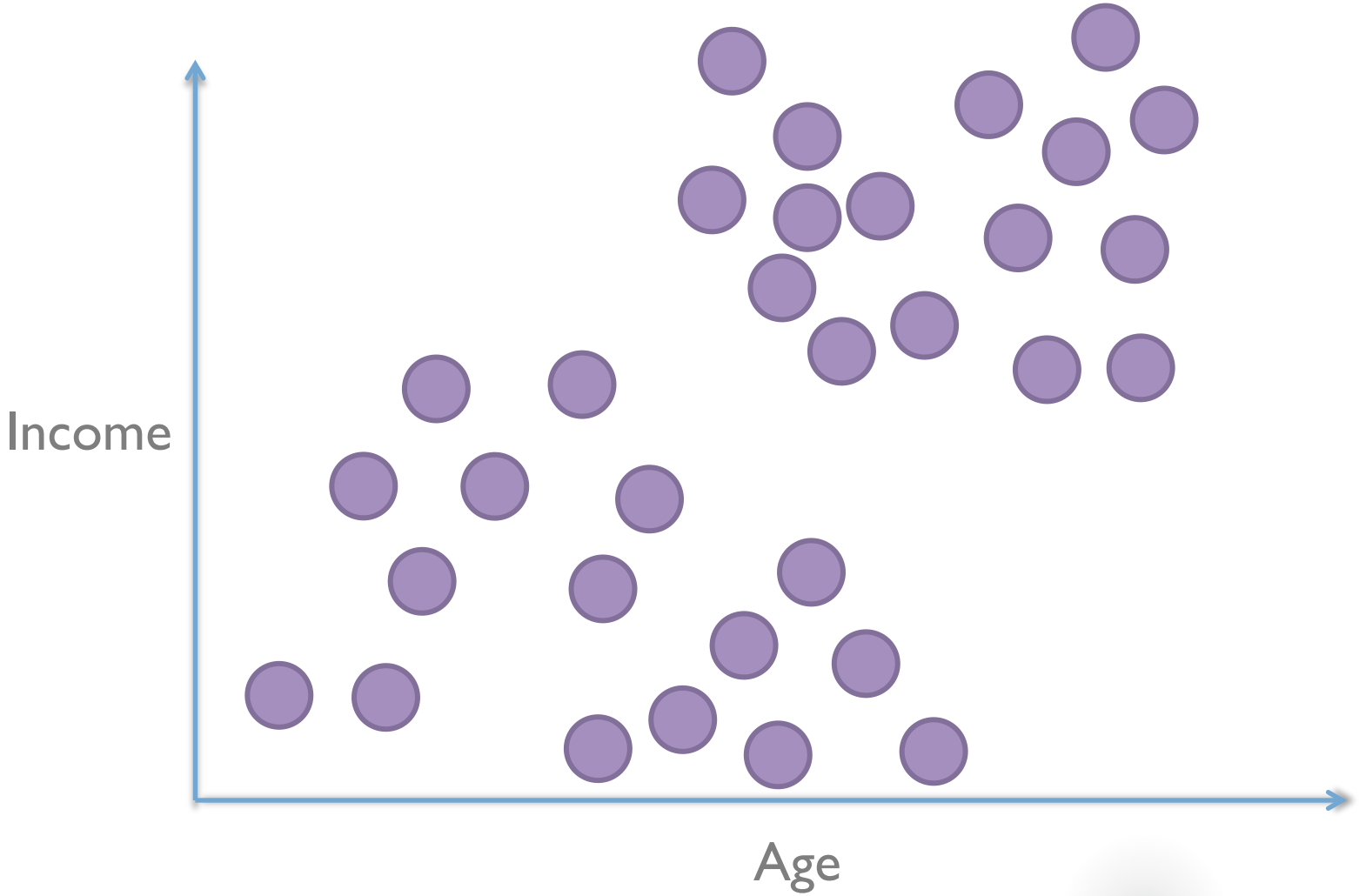
Jaccard dist $= 1 - 3/9 / = 1 - 0.333 = 0.667$

Back to Other Clustering Algorithms

DBSCAN

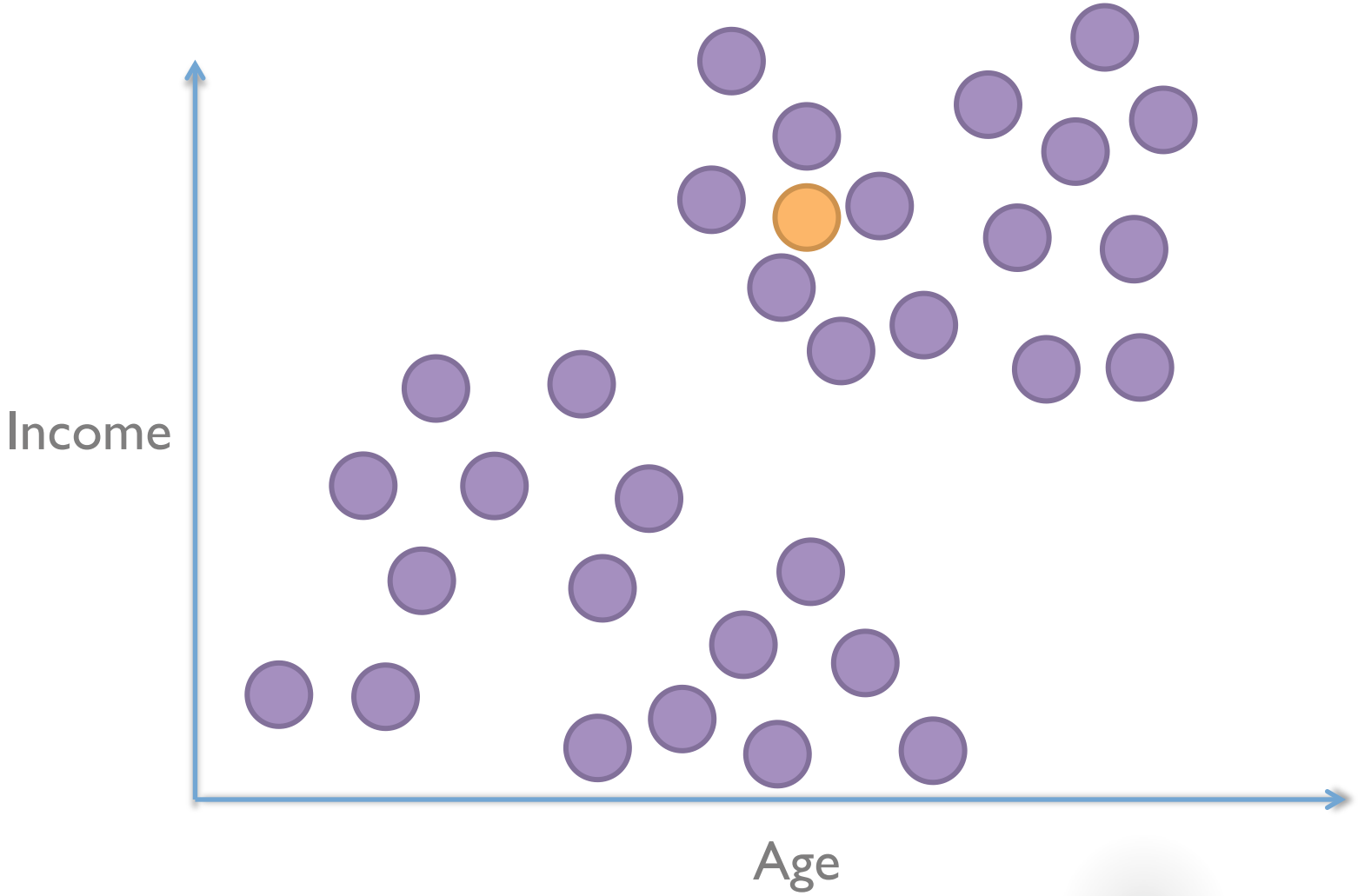
DBSCAN

Density---based spatial clustering of applications with noise



DBSCAN

Start at a random point

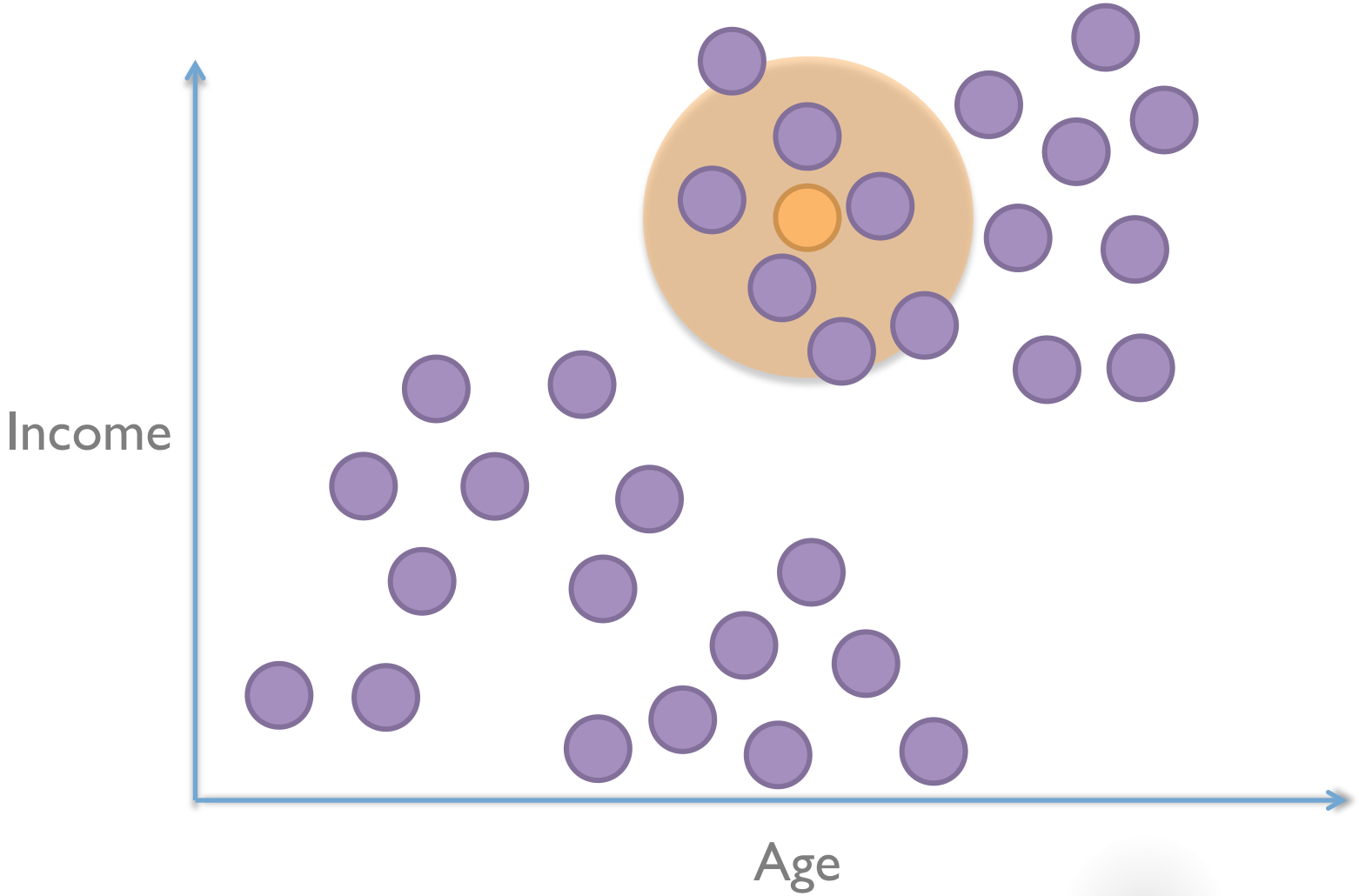


epsilon = 1.75
n_clu = 3

DBSCAN

Look at the radius *epsilon* around point

If enough points (*n_clu*) within circle, start cluster

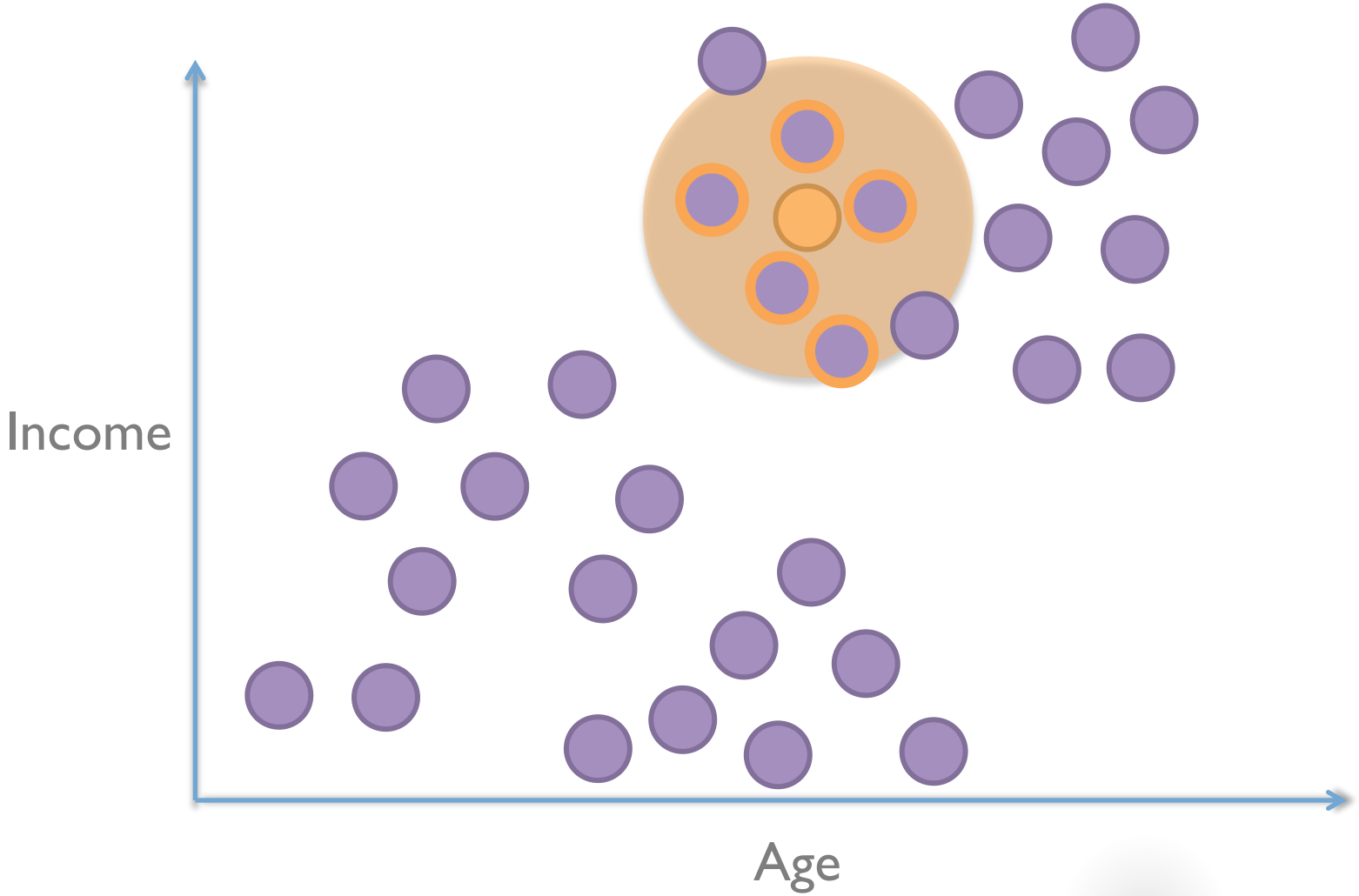


epsilon = 1.75
n_clu = 3

DBSCAN

Everybody within *epsilon* are part of the cluster.

Process each the same way.



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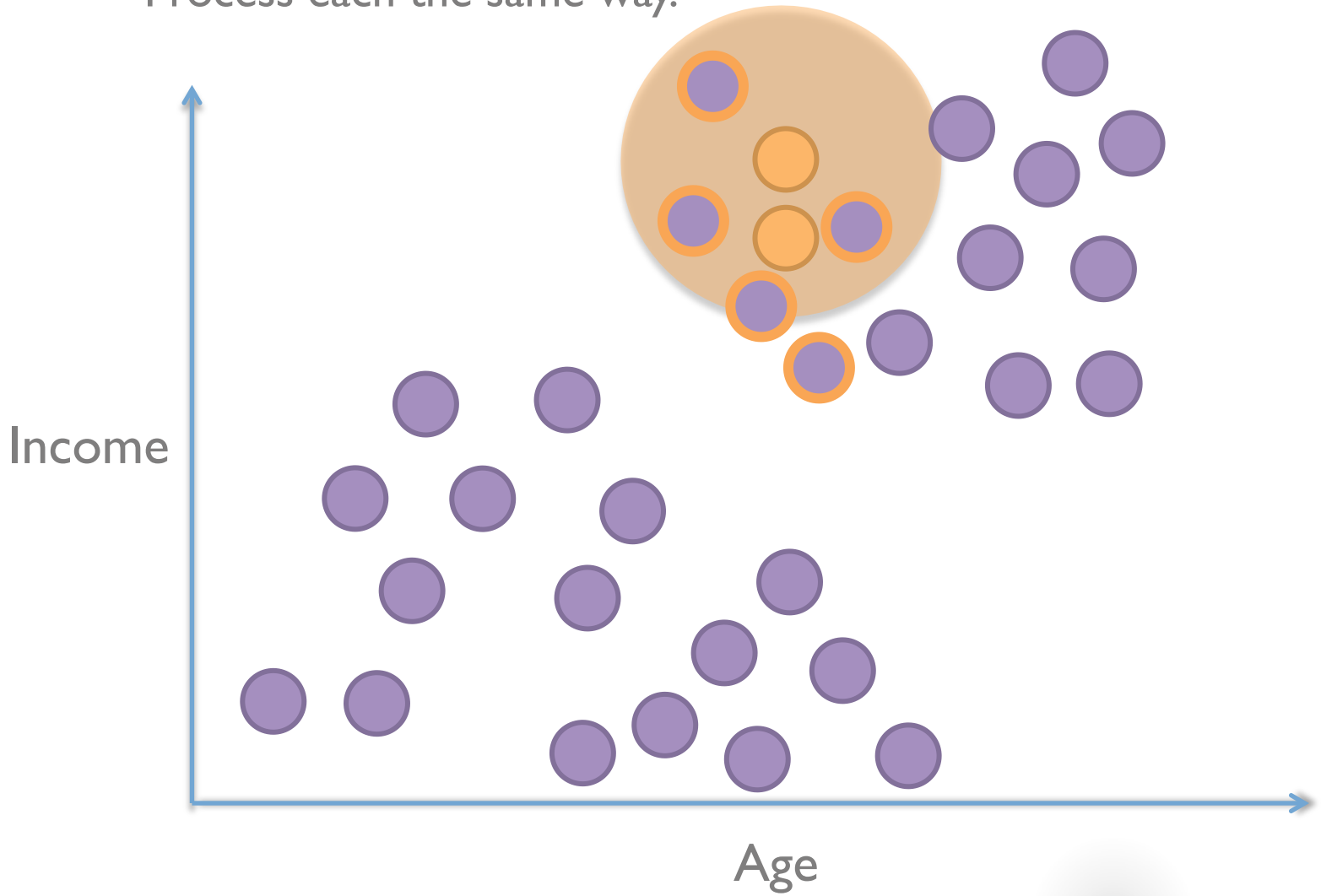

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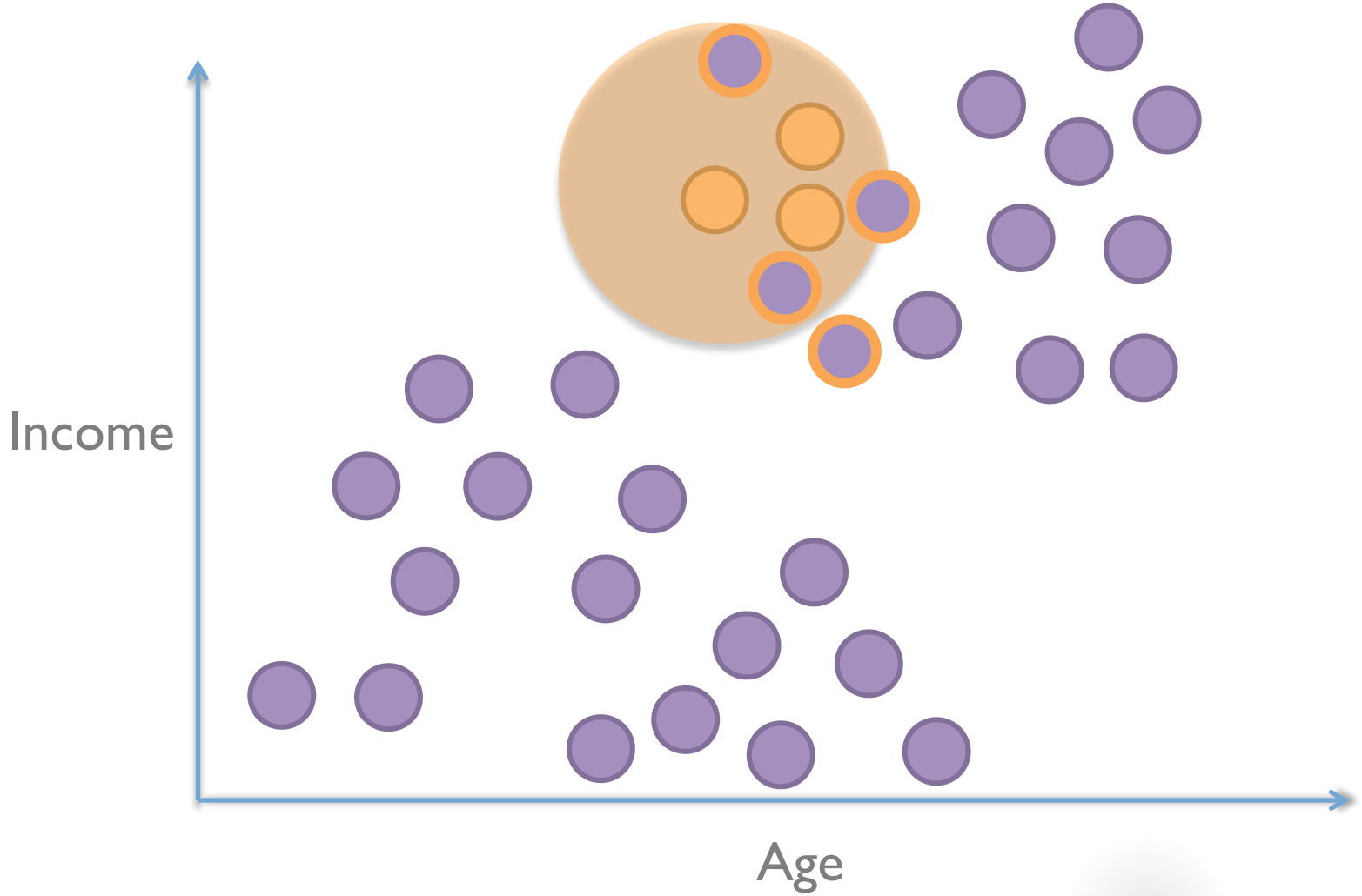

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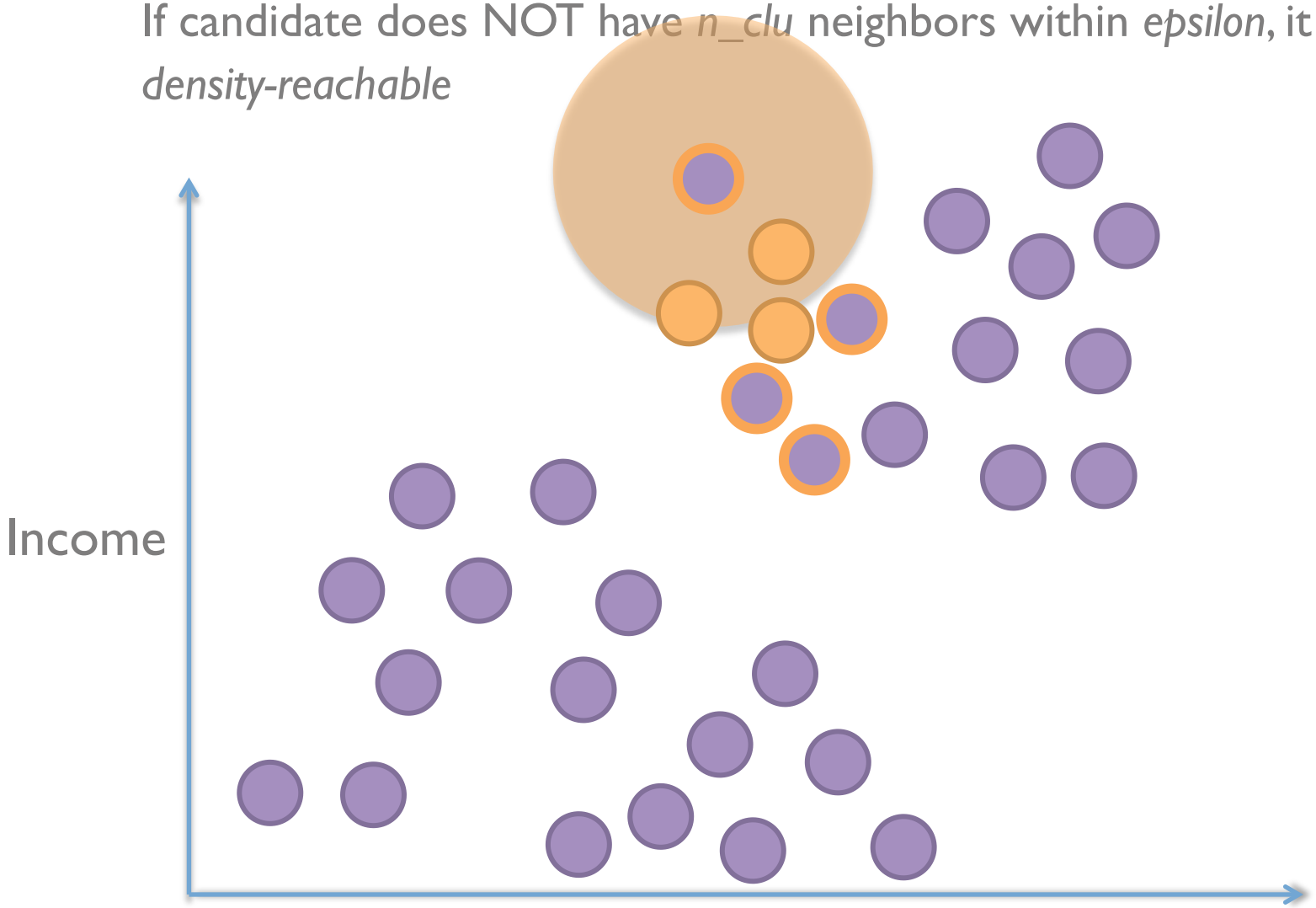
DBSCAN

If candidate does NOT have *n_clu* neighbors within *epsilon*, it is *density-reachable*



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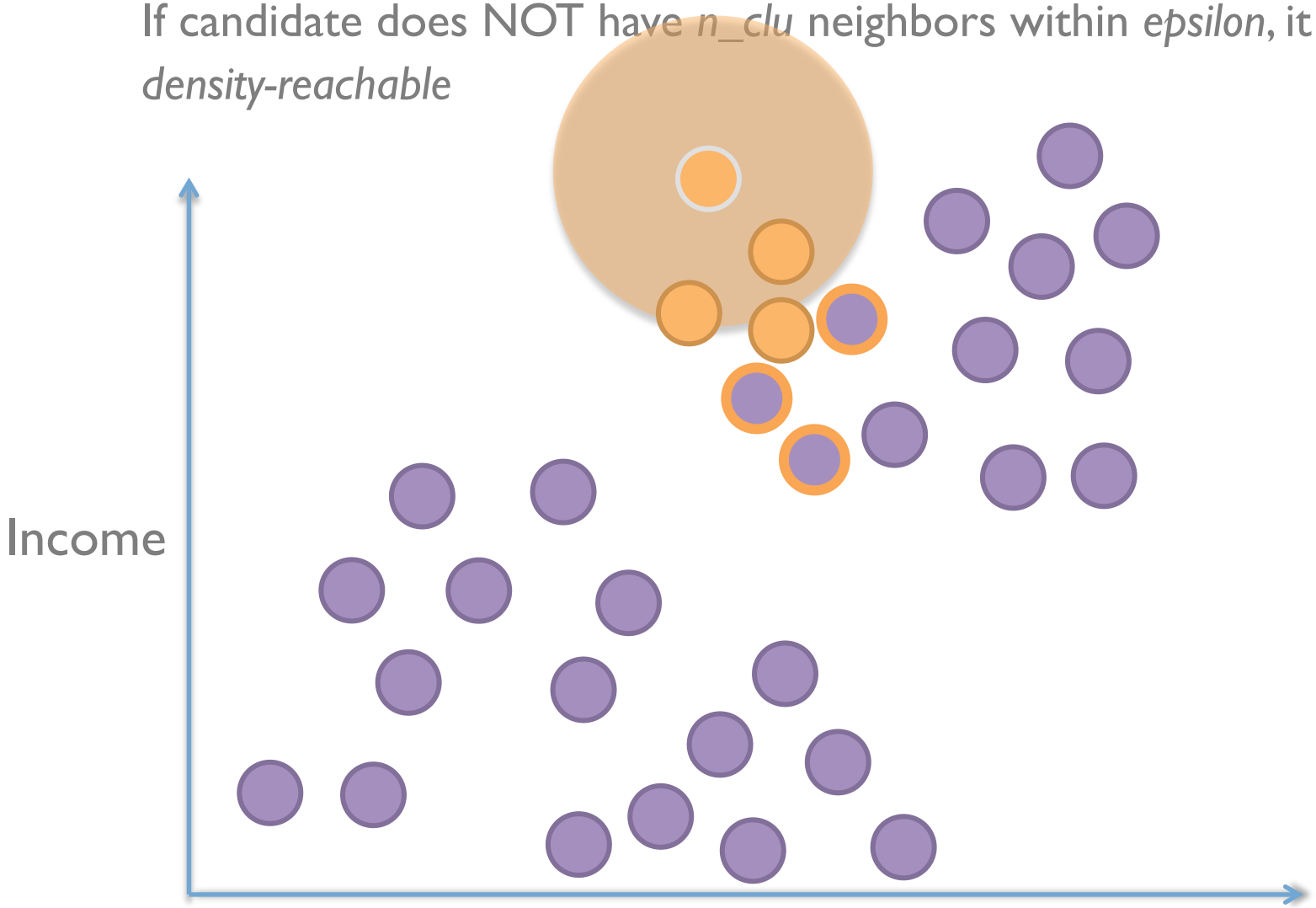

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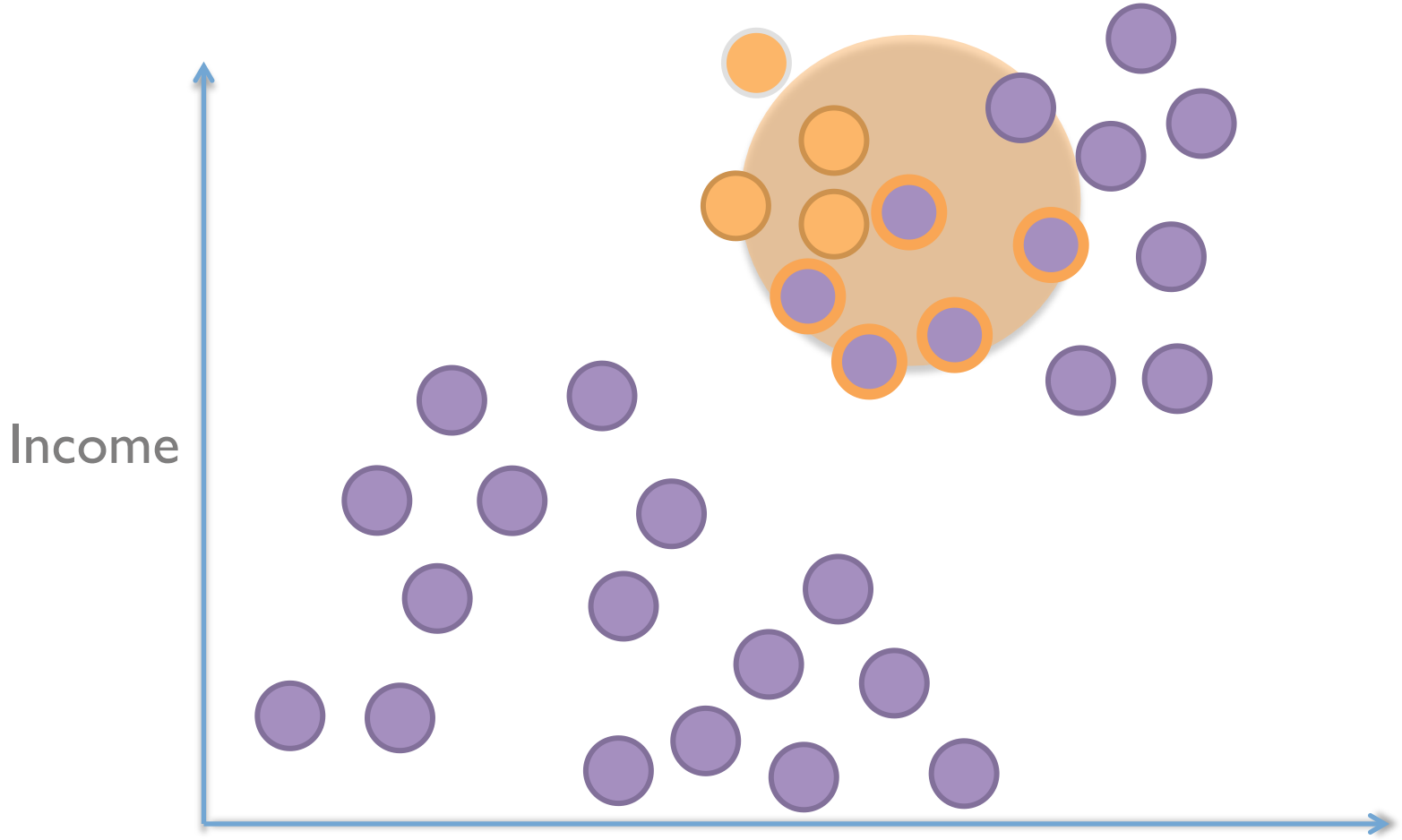
DBSCAN

Keep going until you find the entire cluster and no point is left unvisited by this chain reaction



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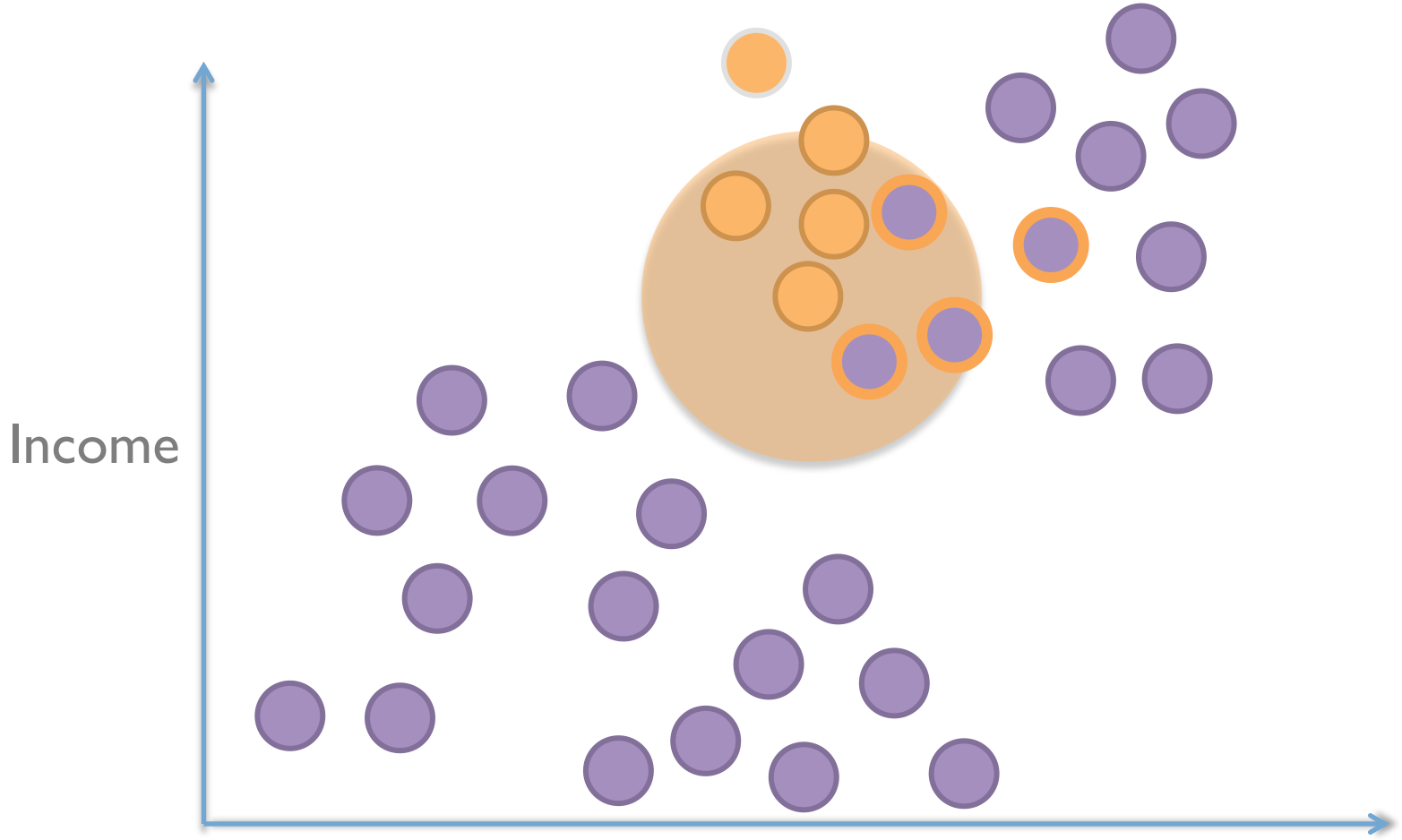

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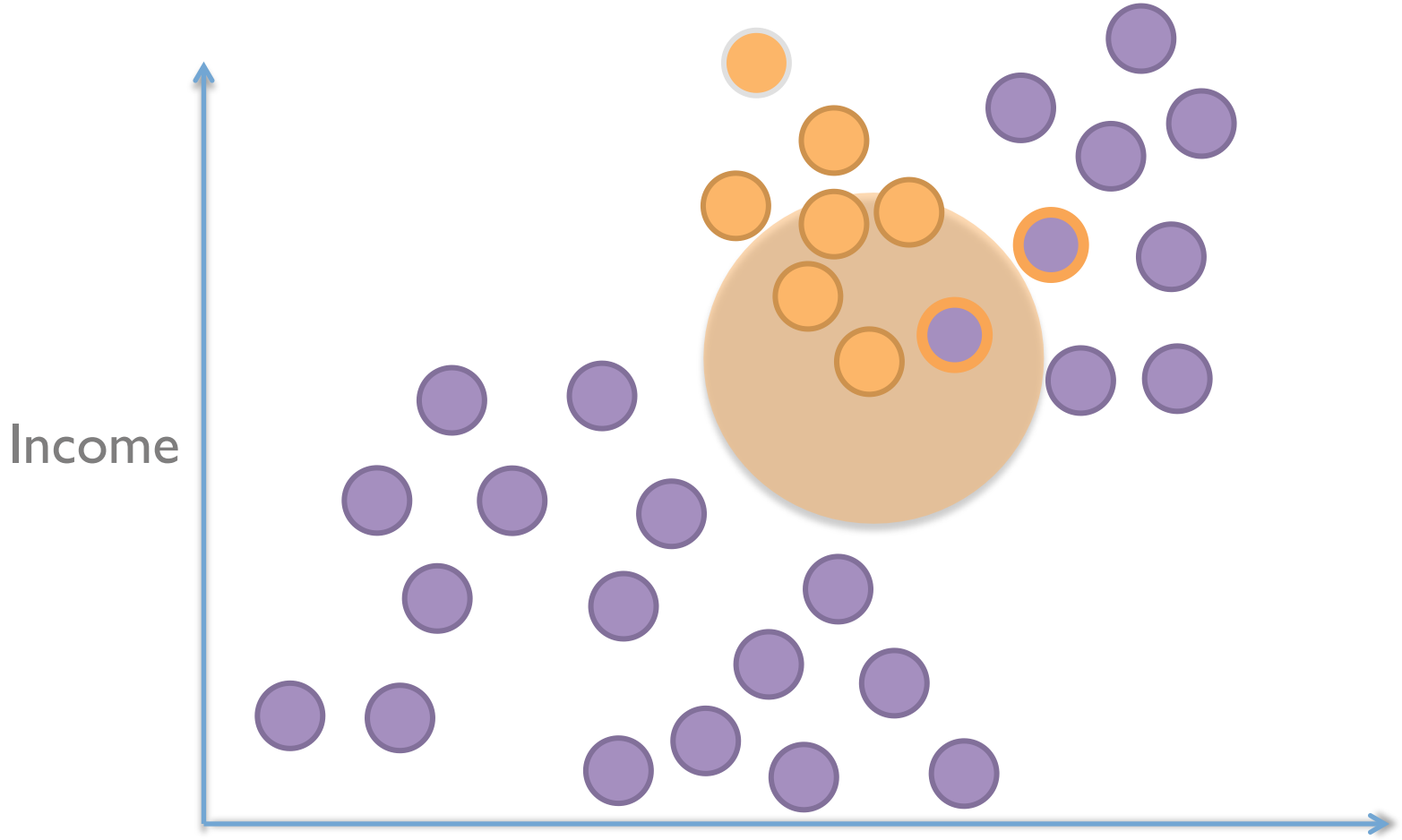

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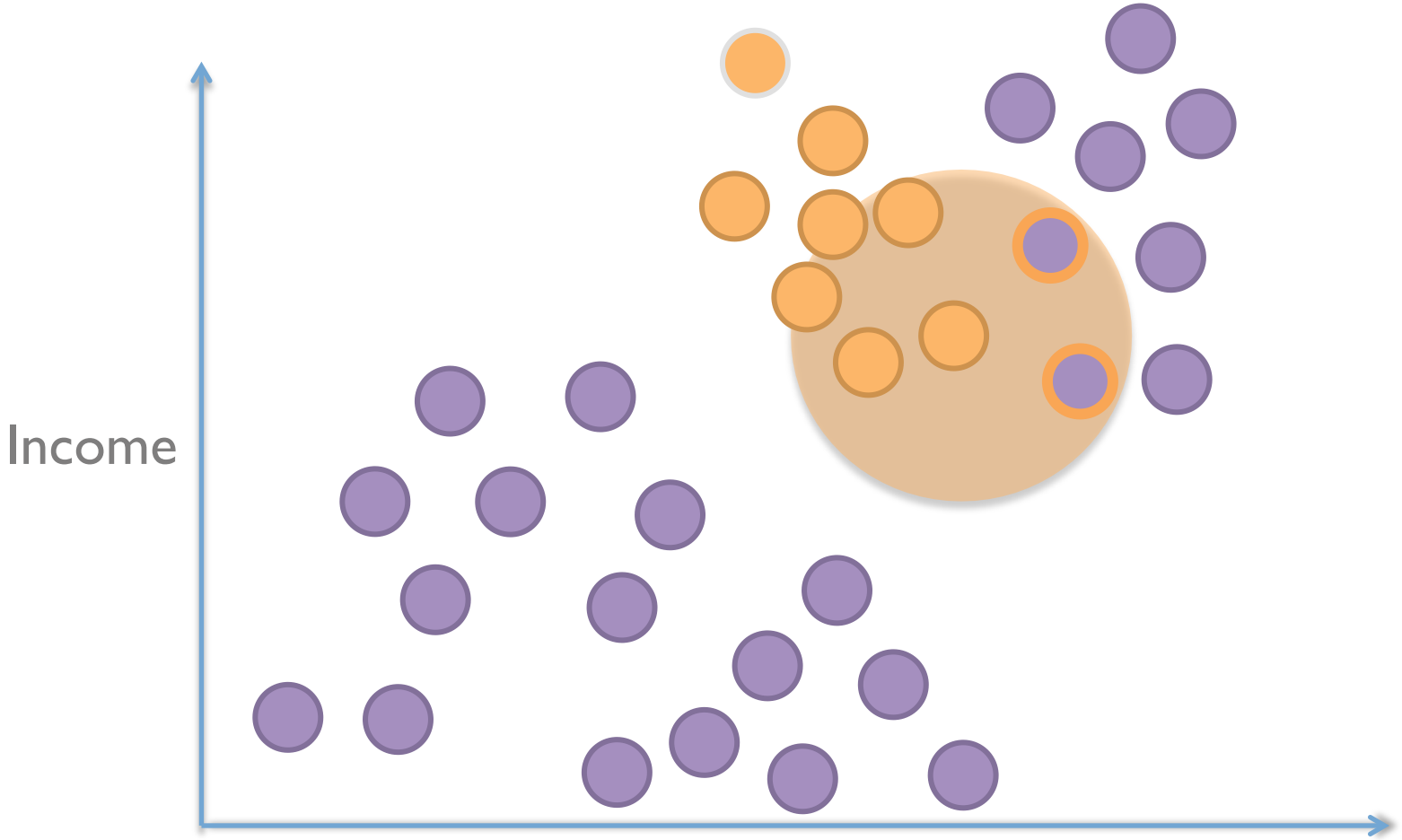

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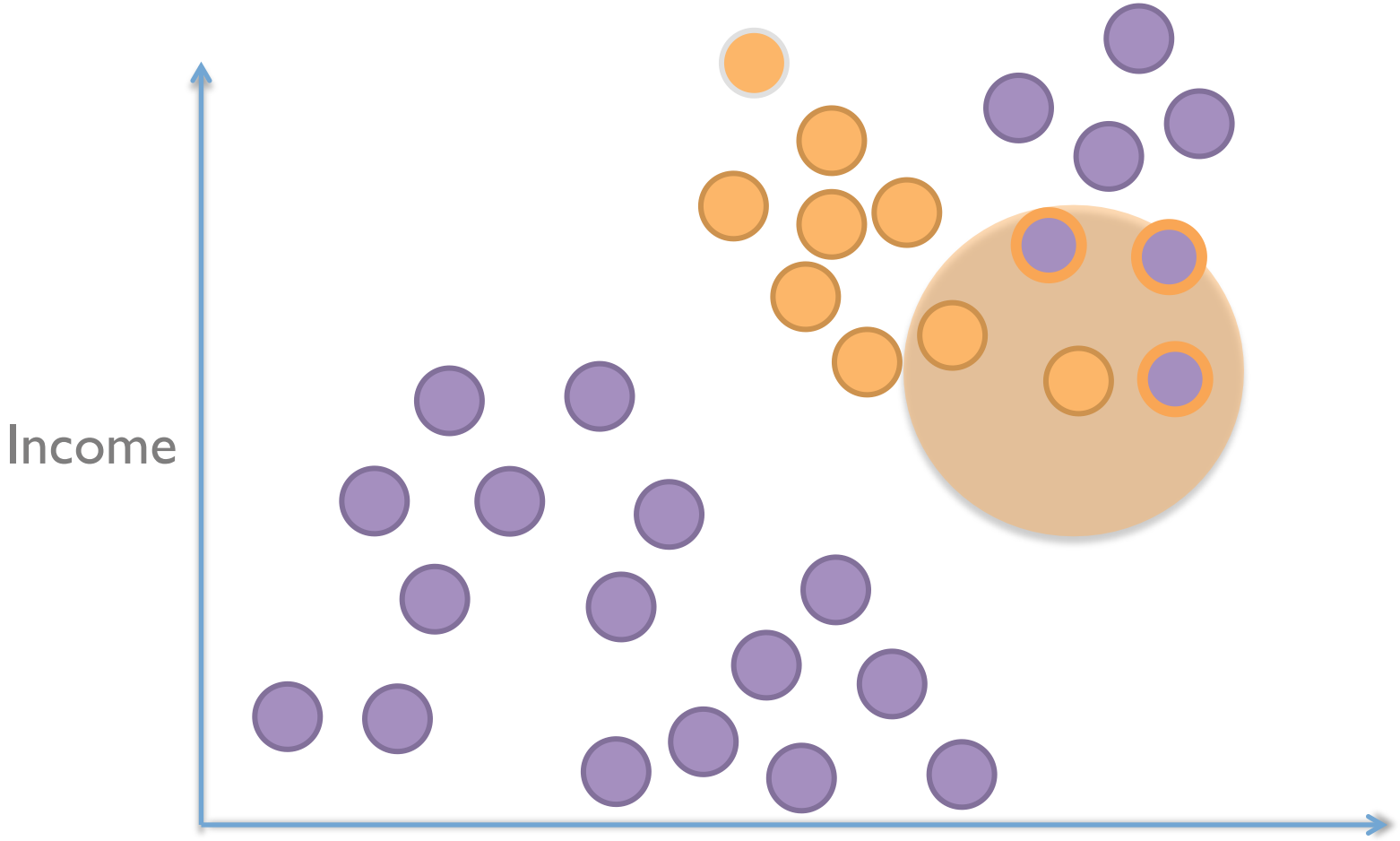

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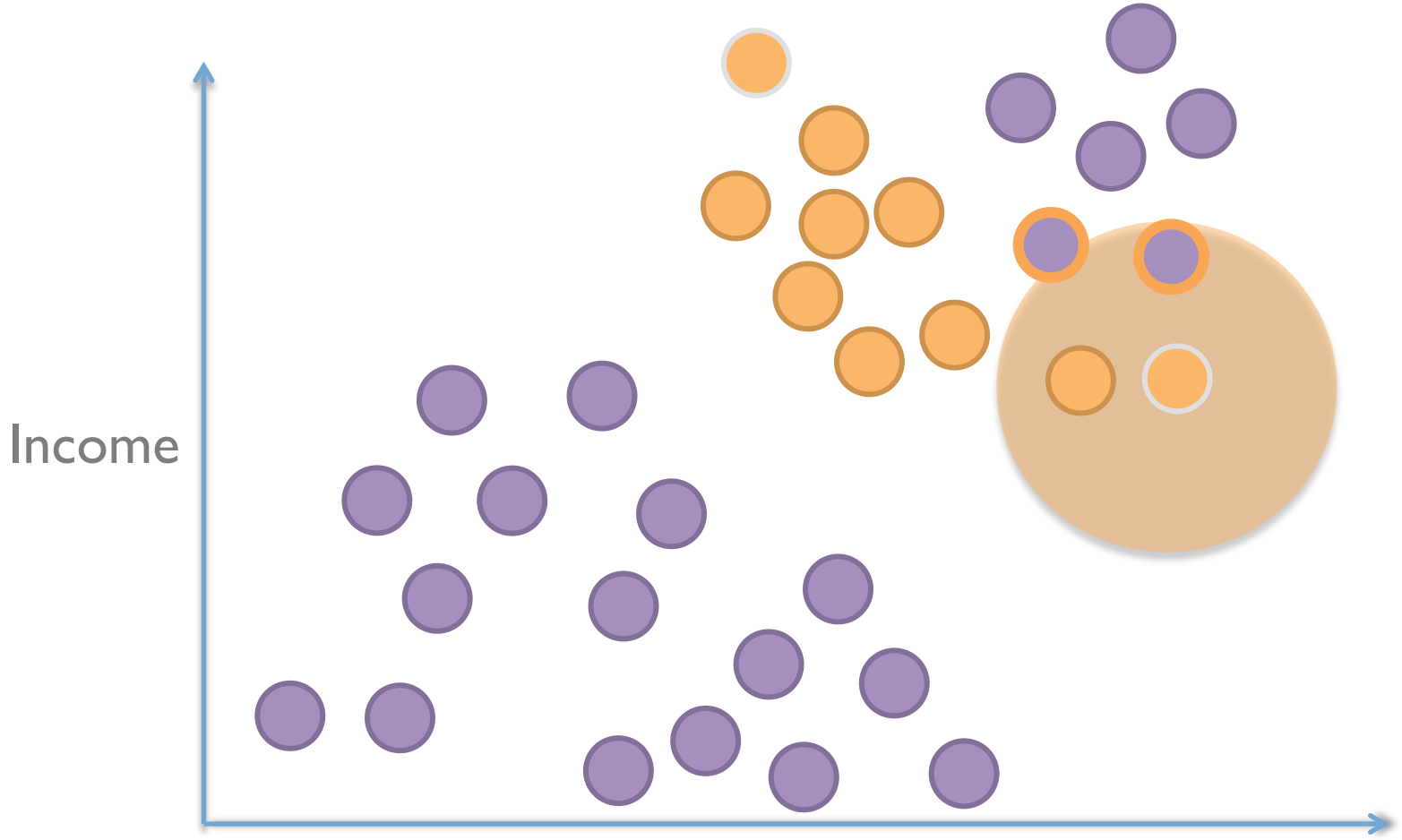

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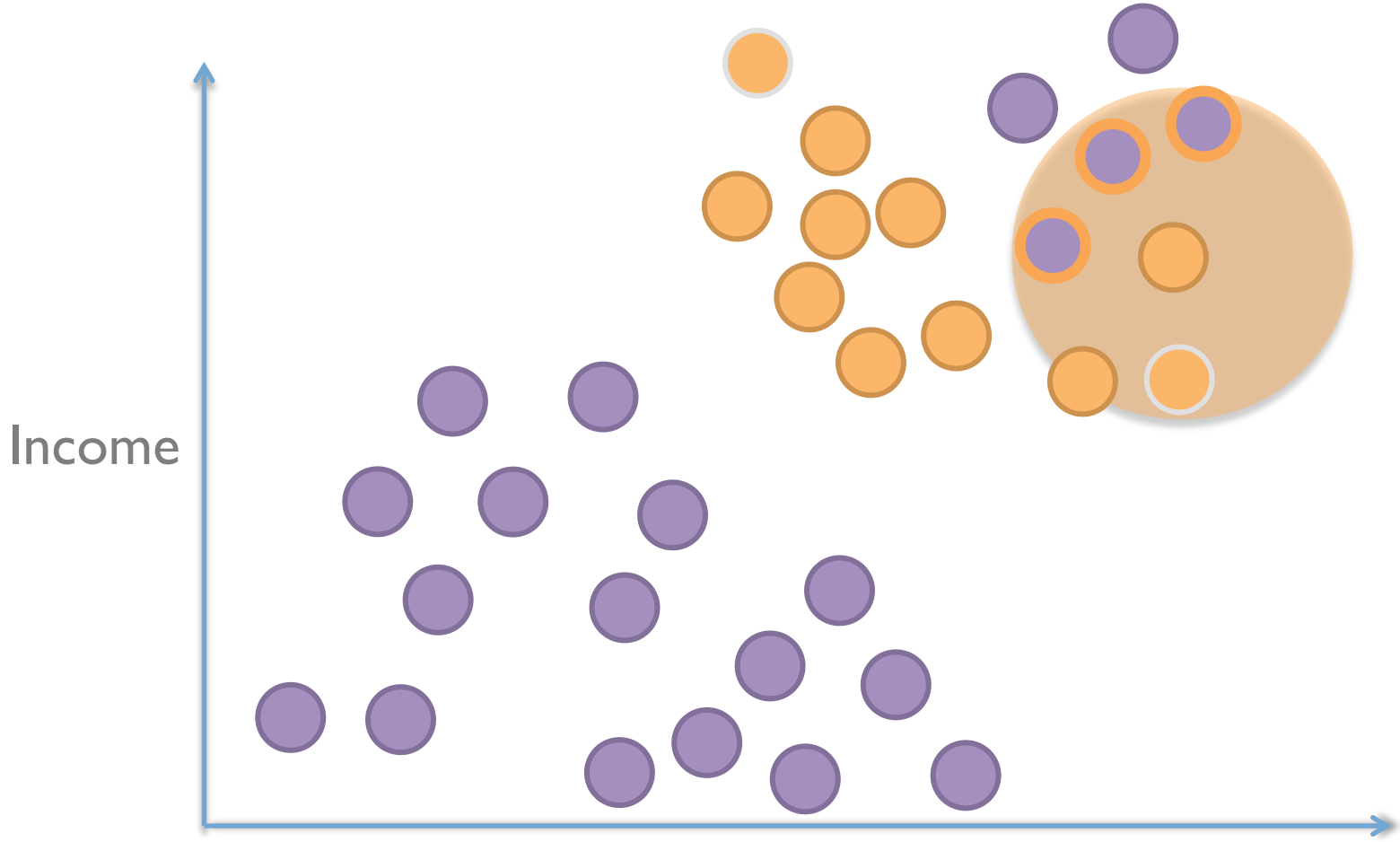

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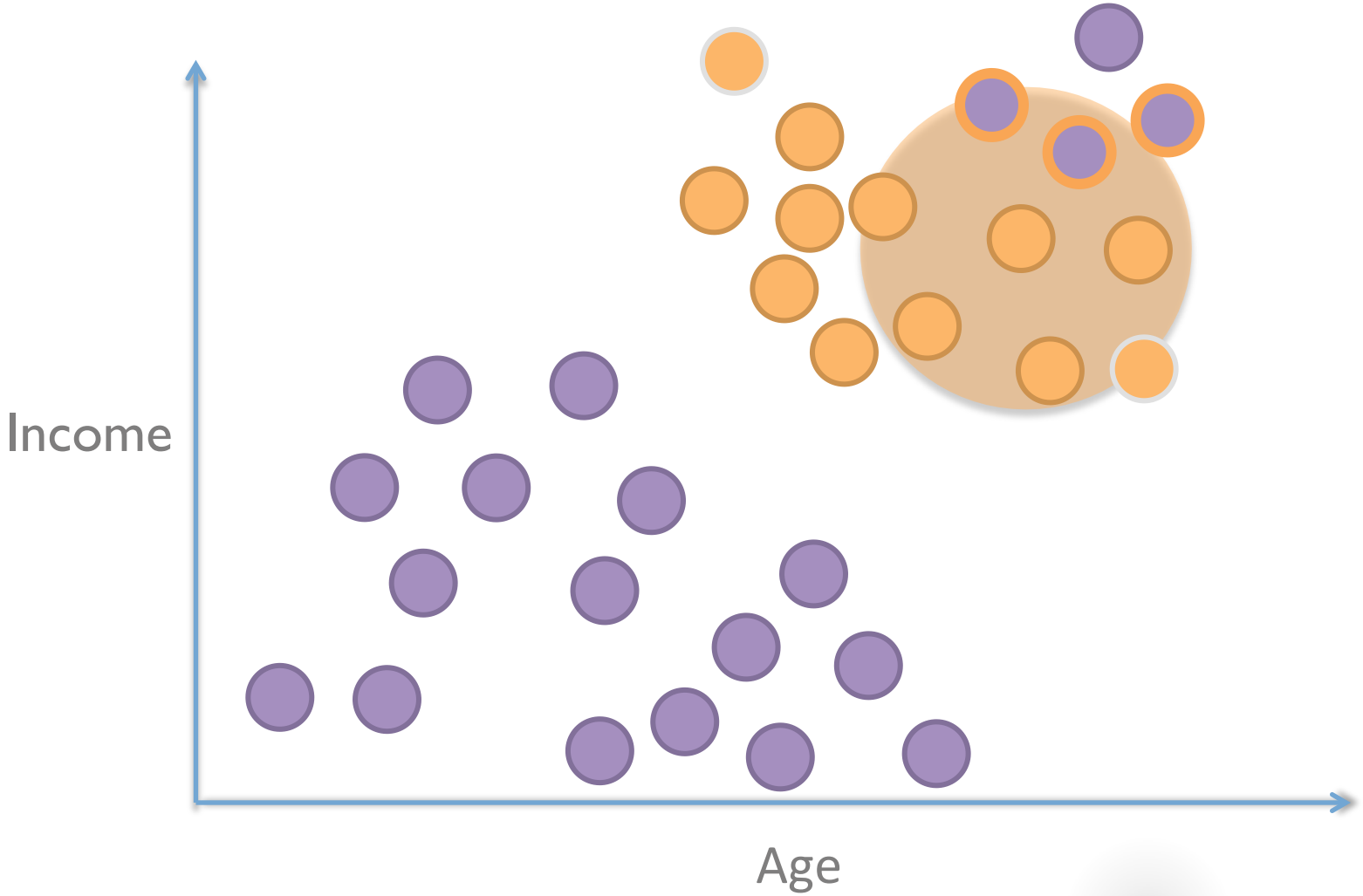

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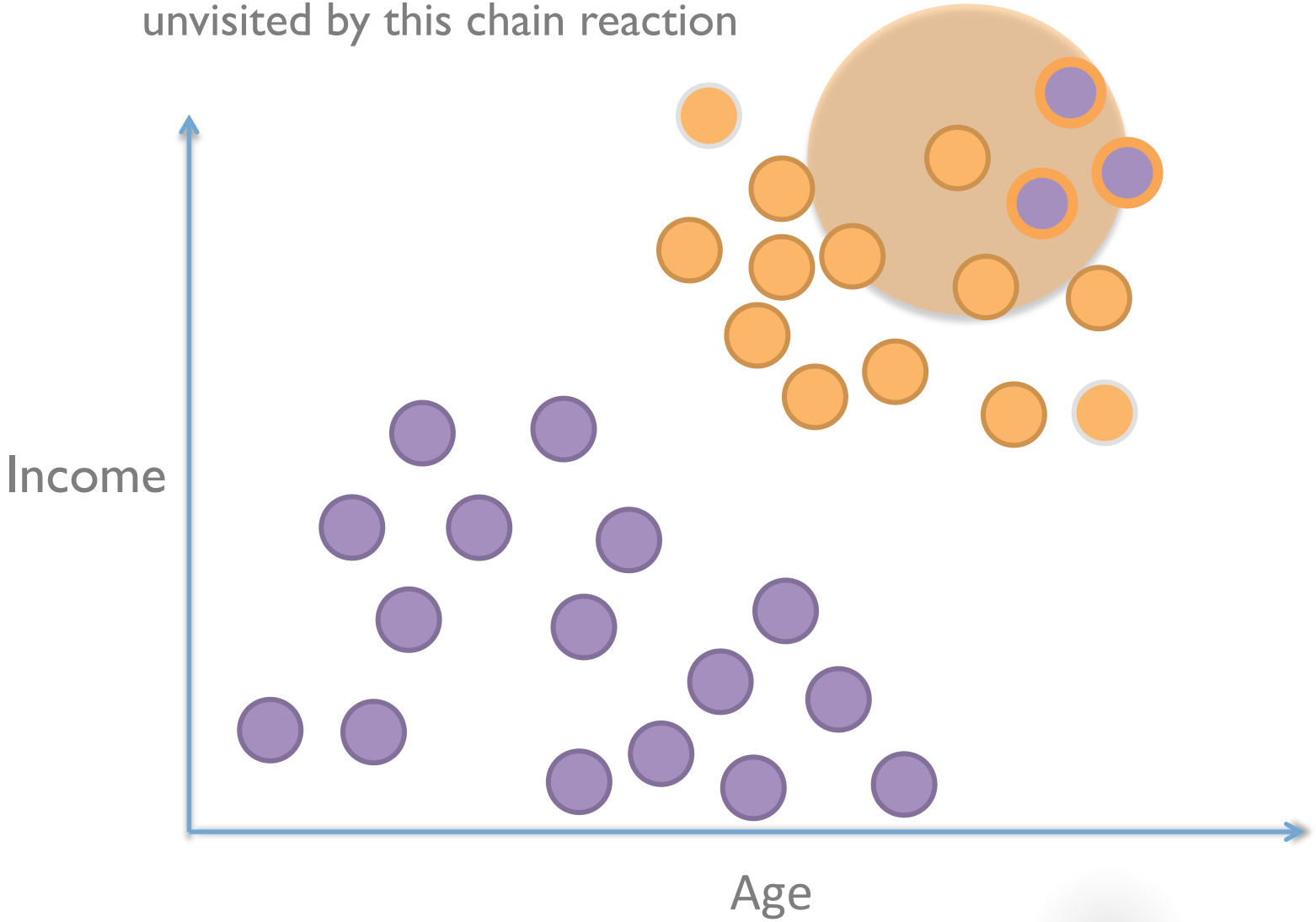

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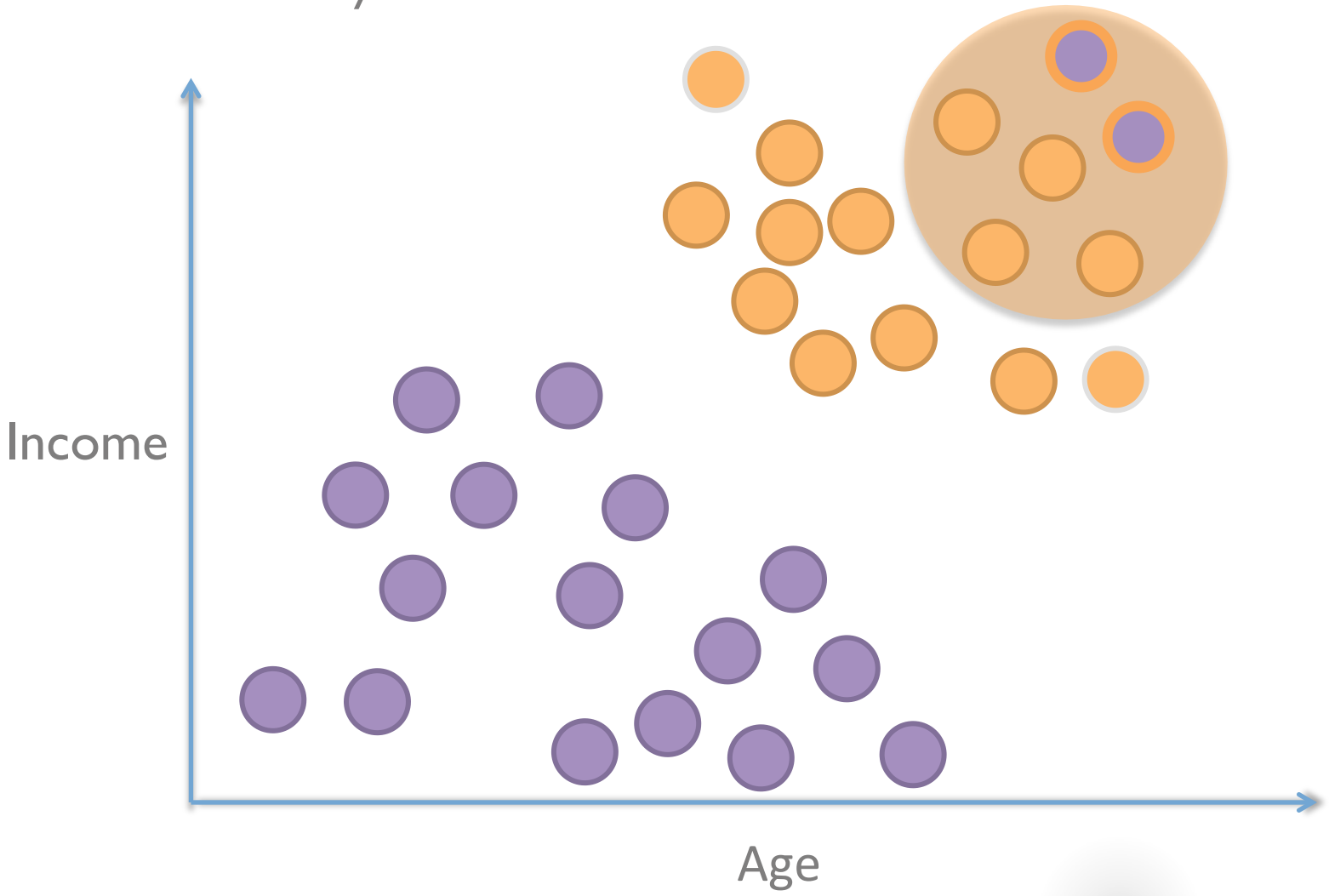

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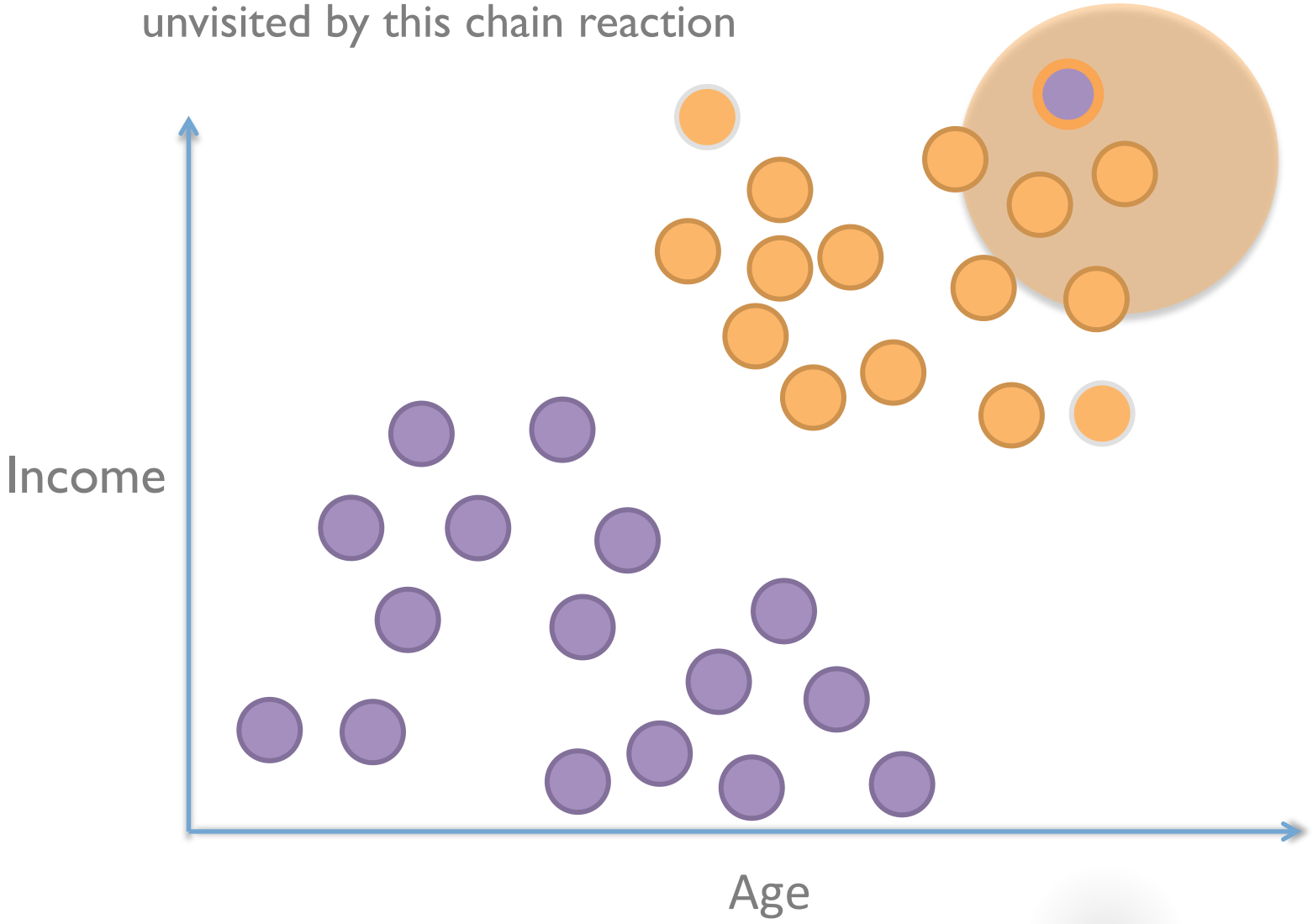

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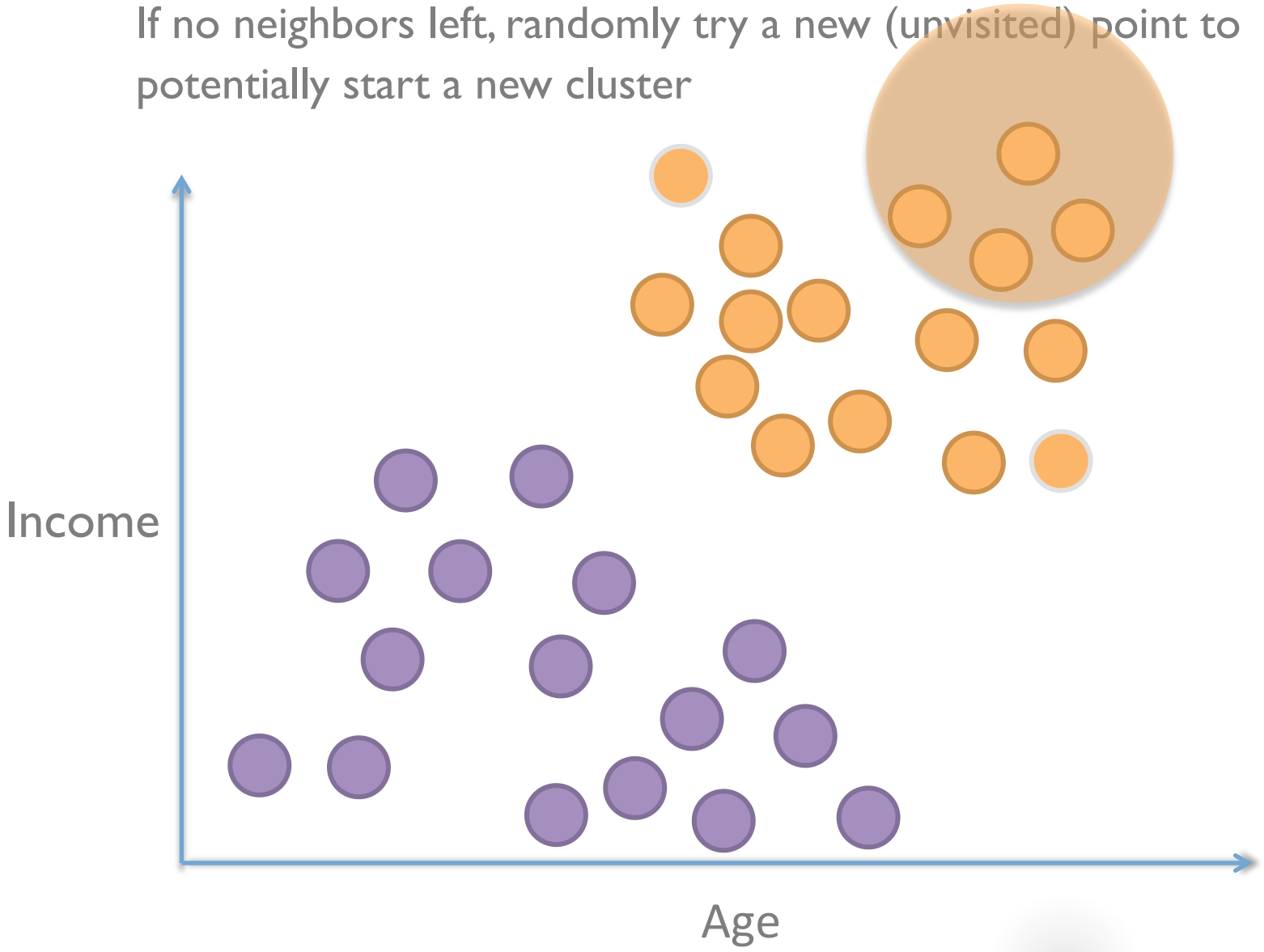

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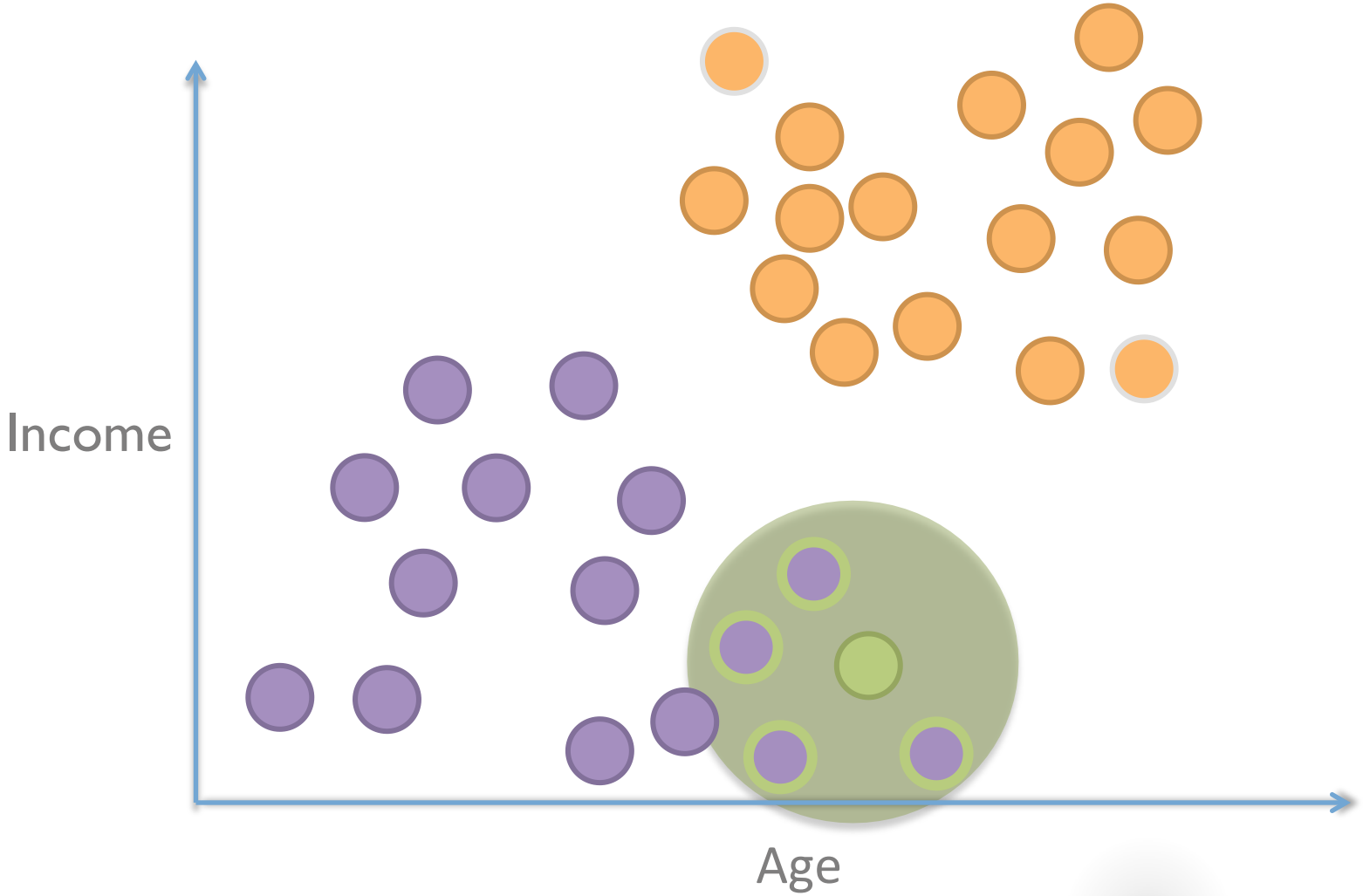

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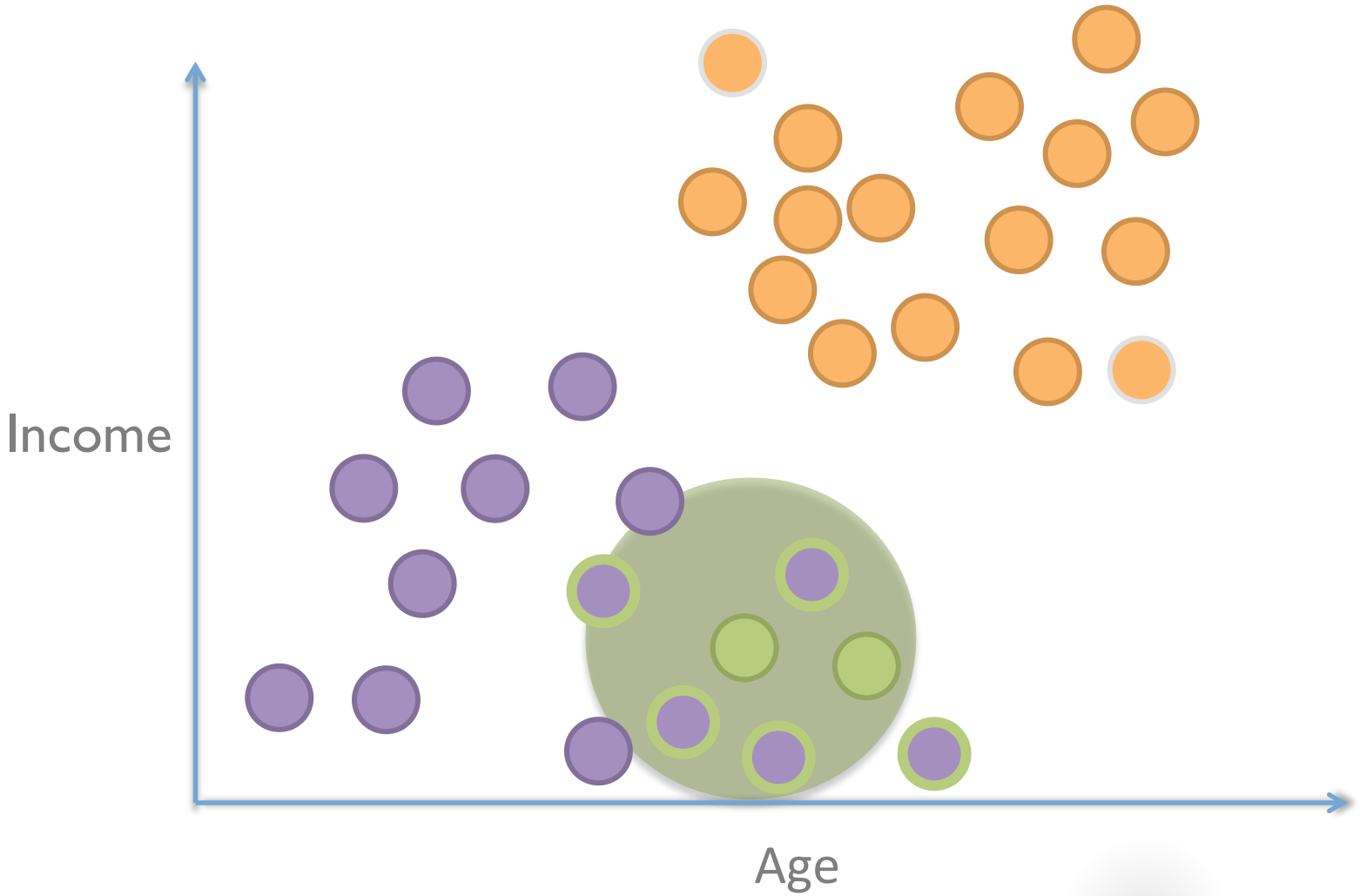
Keep adding neighbors within *epsilon* as chain reaction



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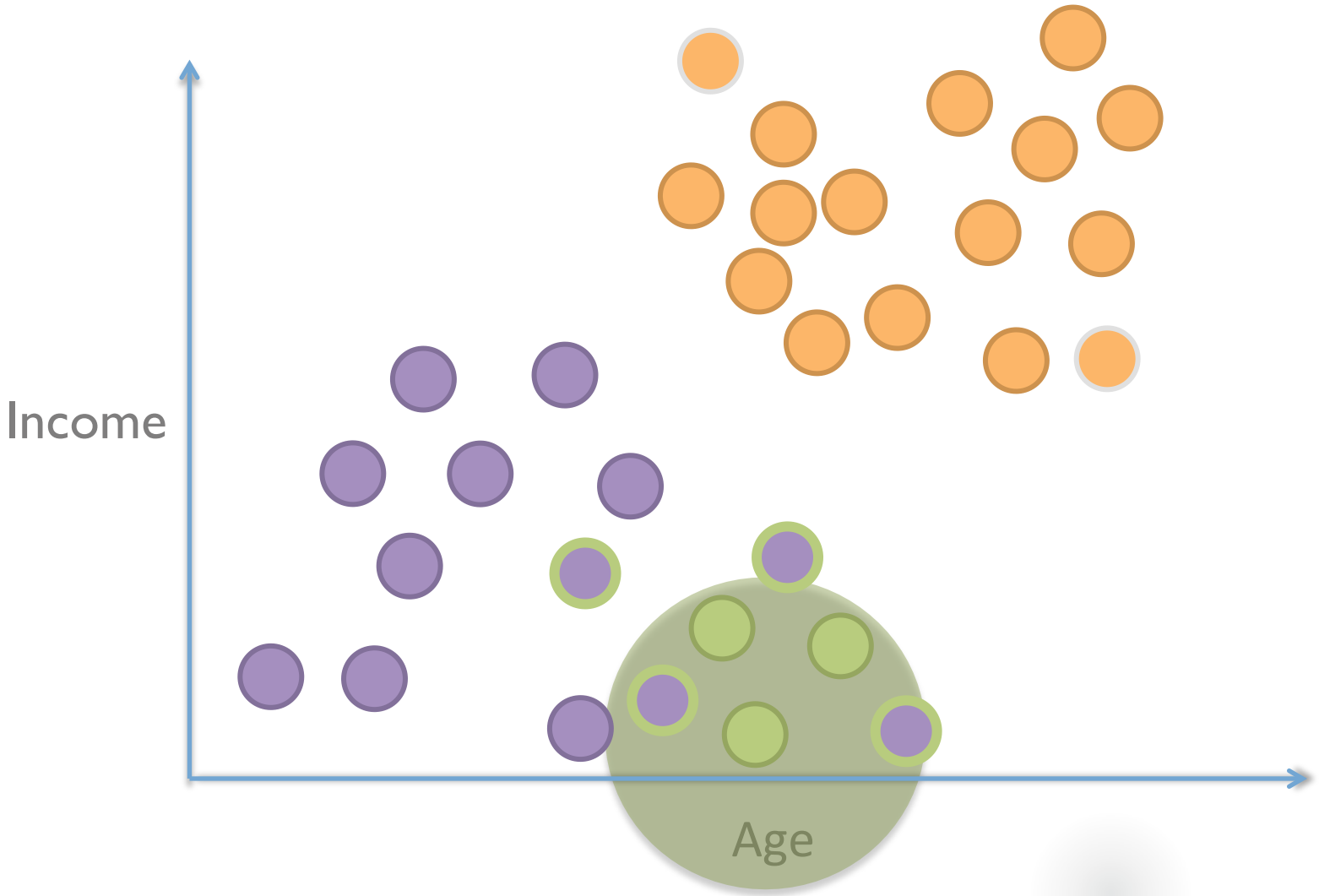

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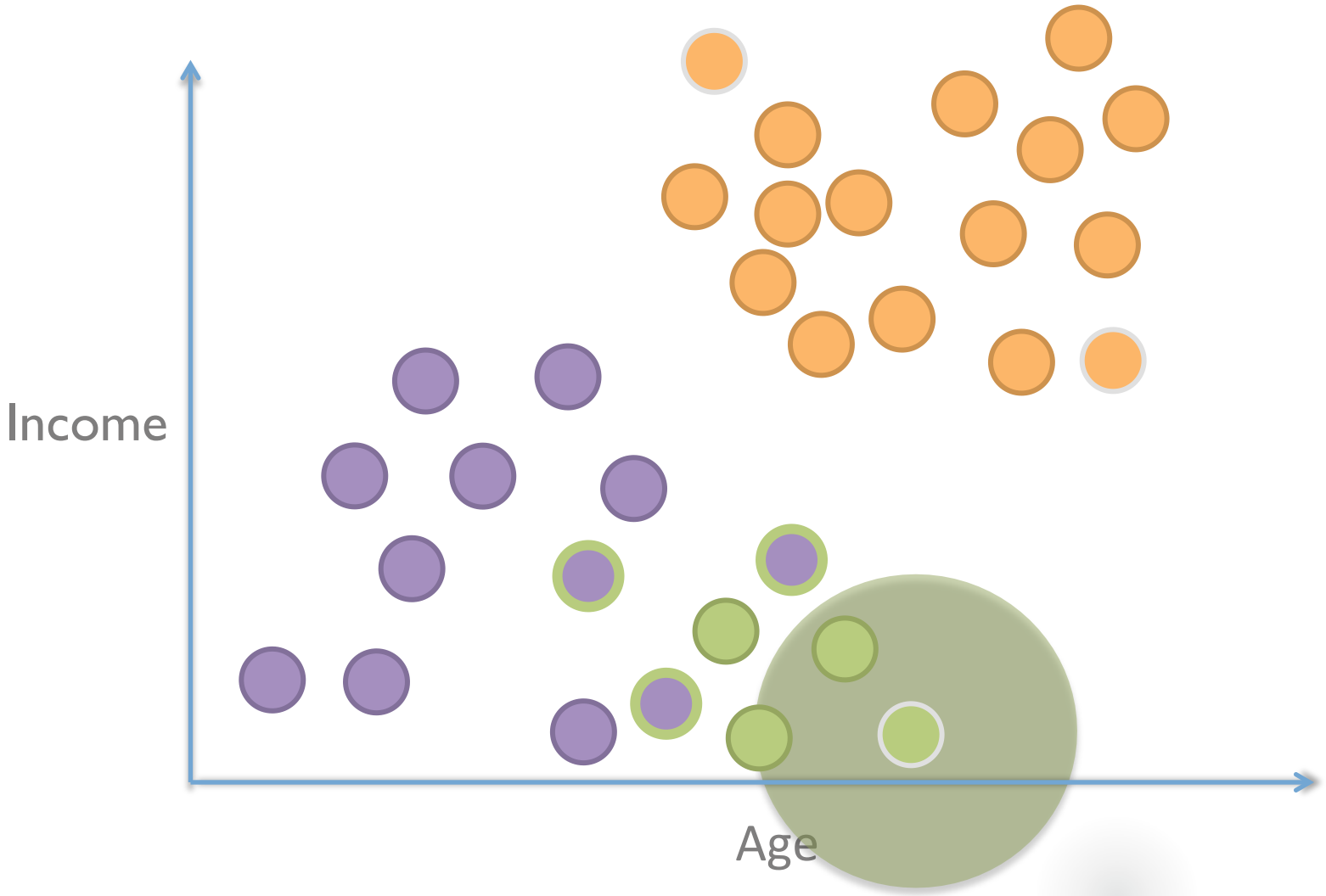

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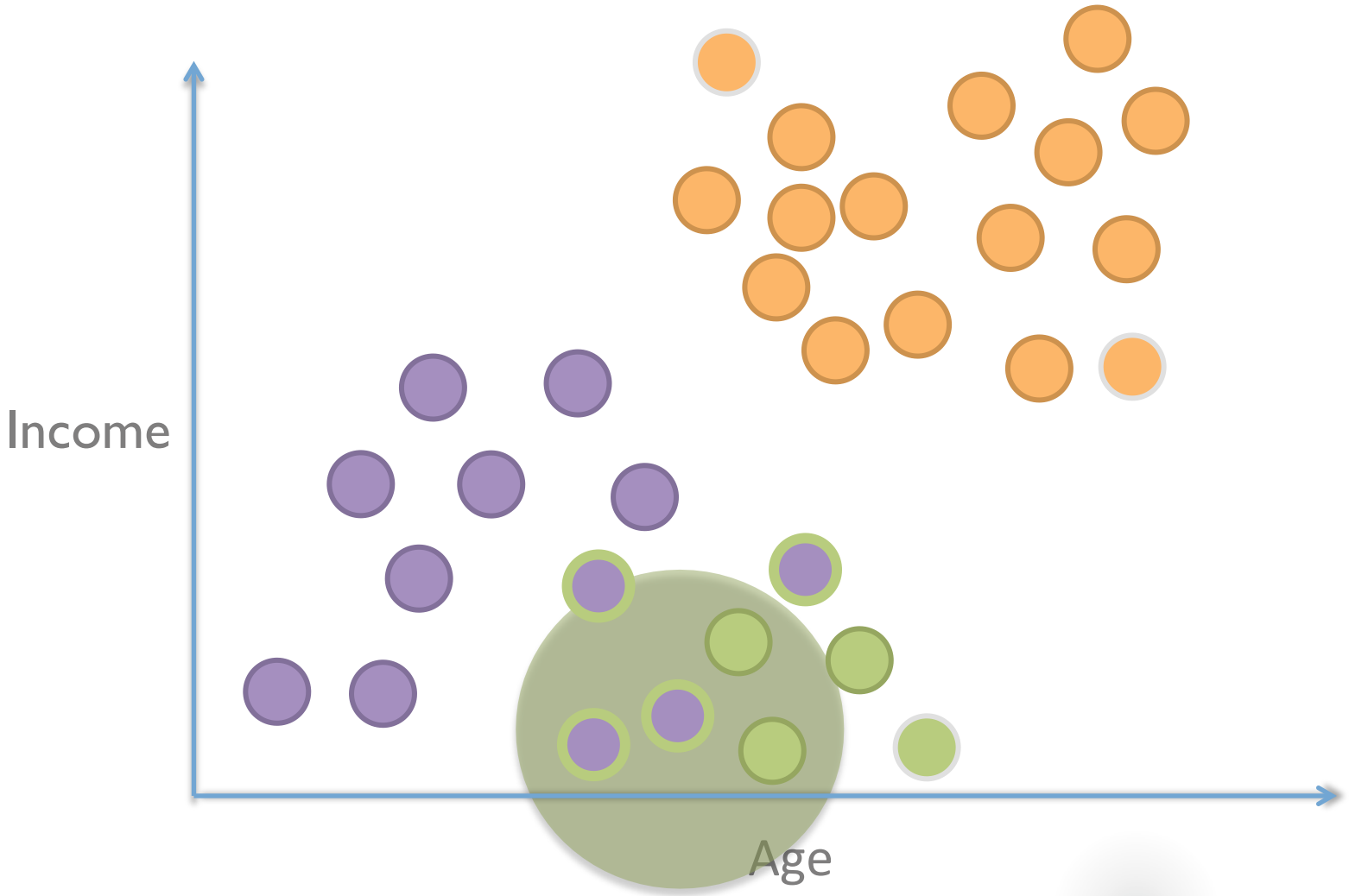

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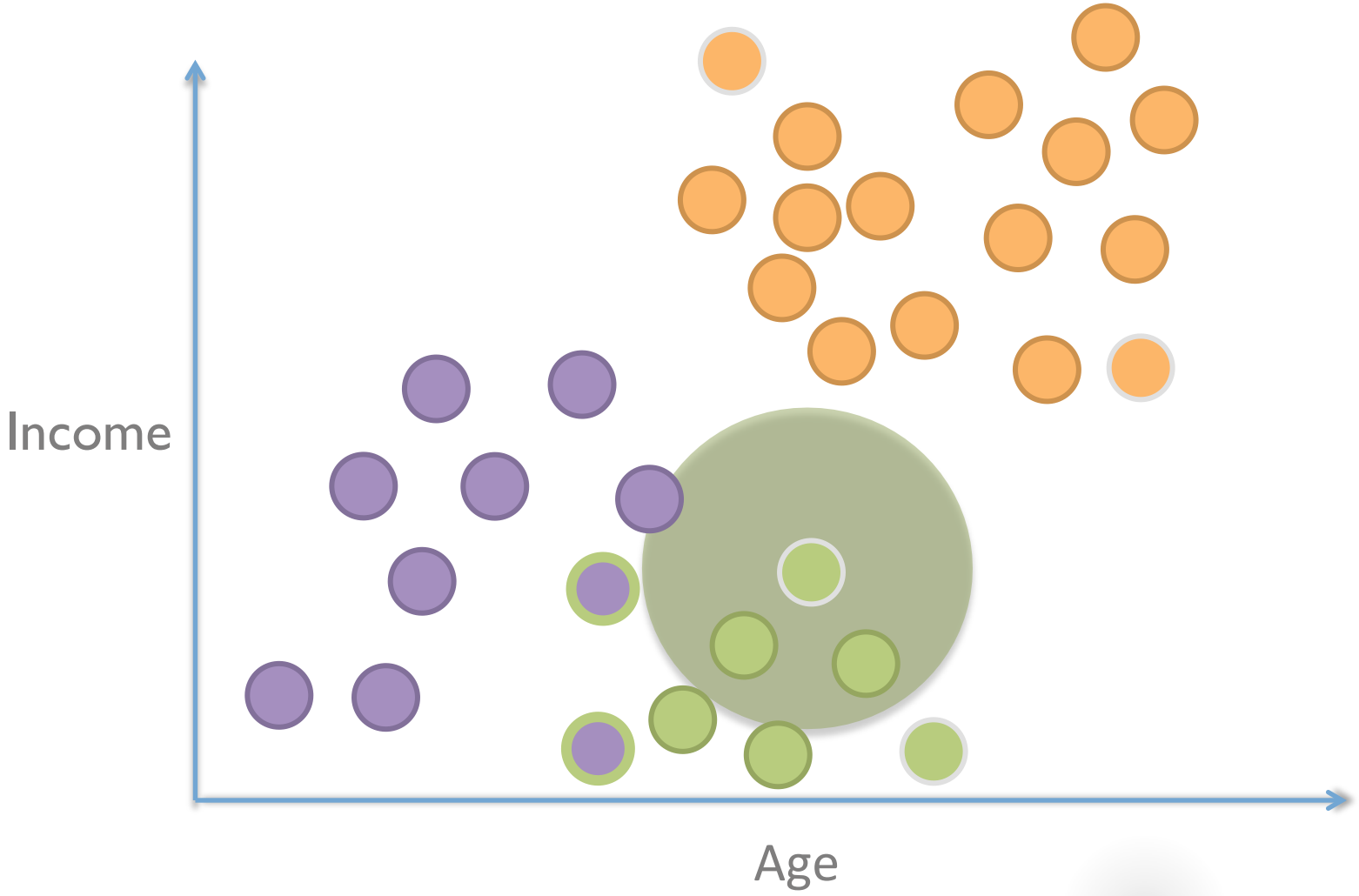

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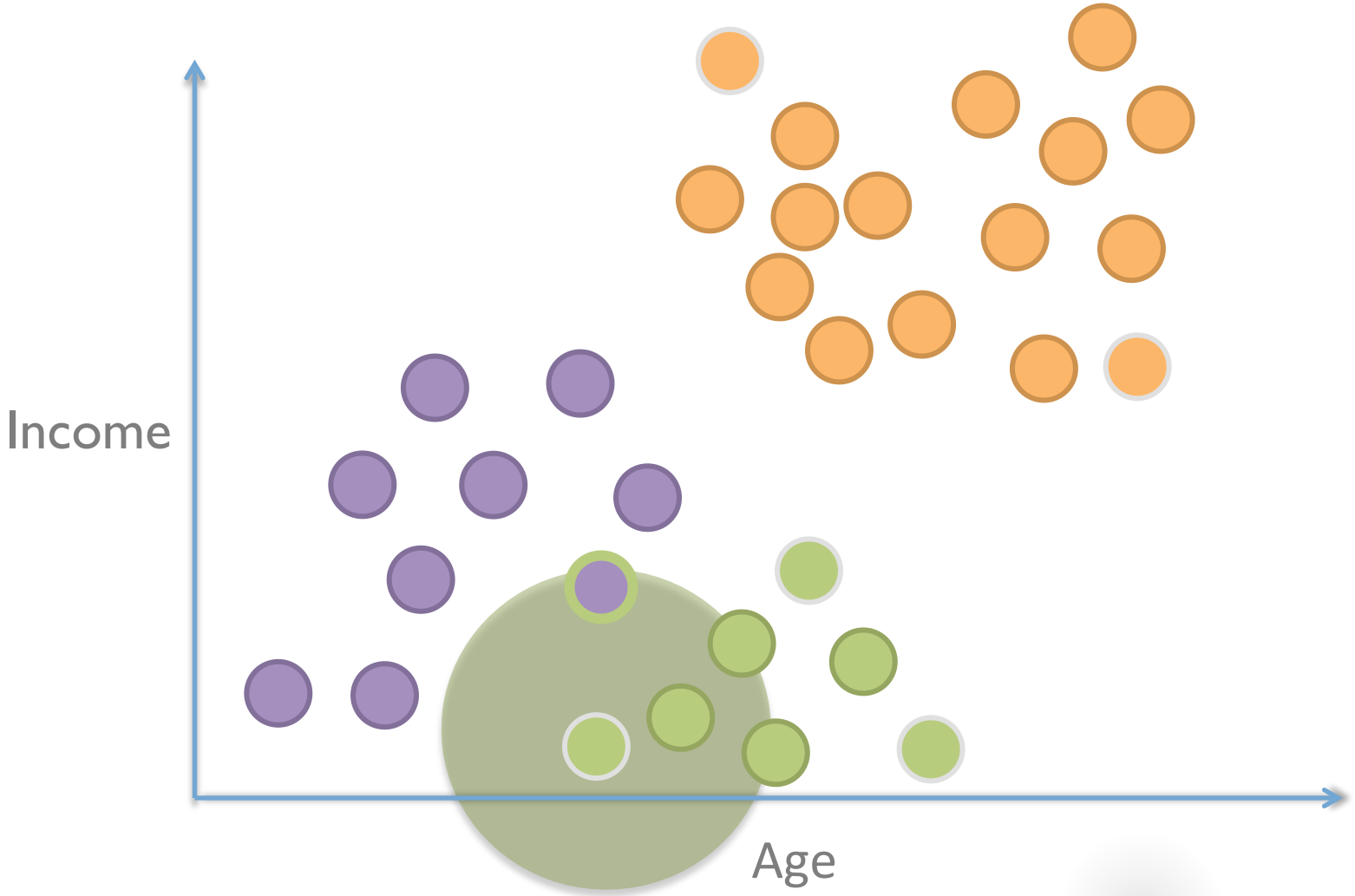

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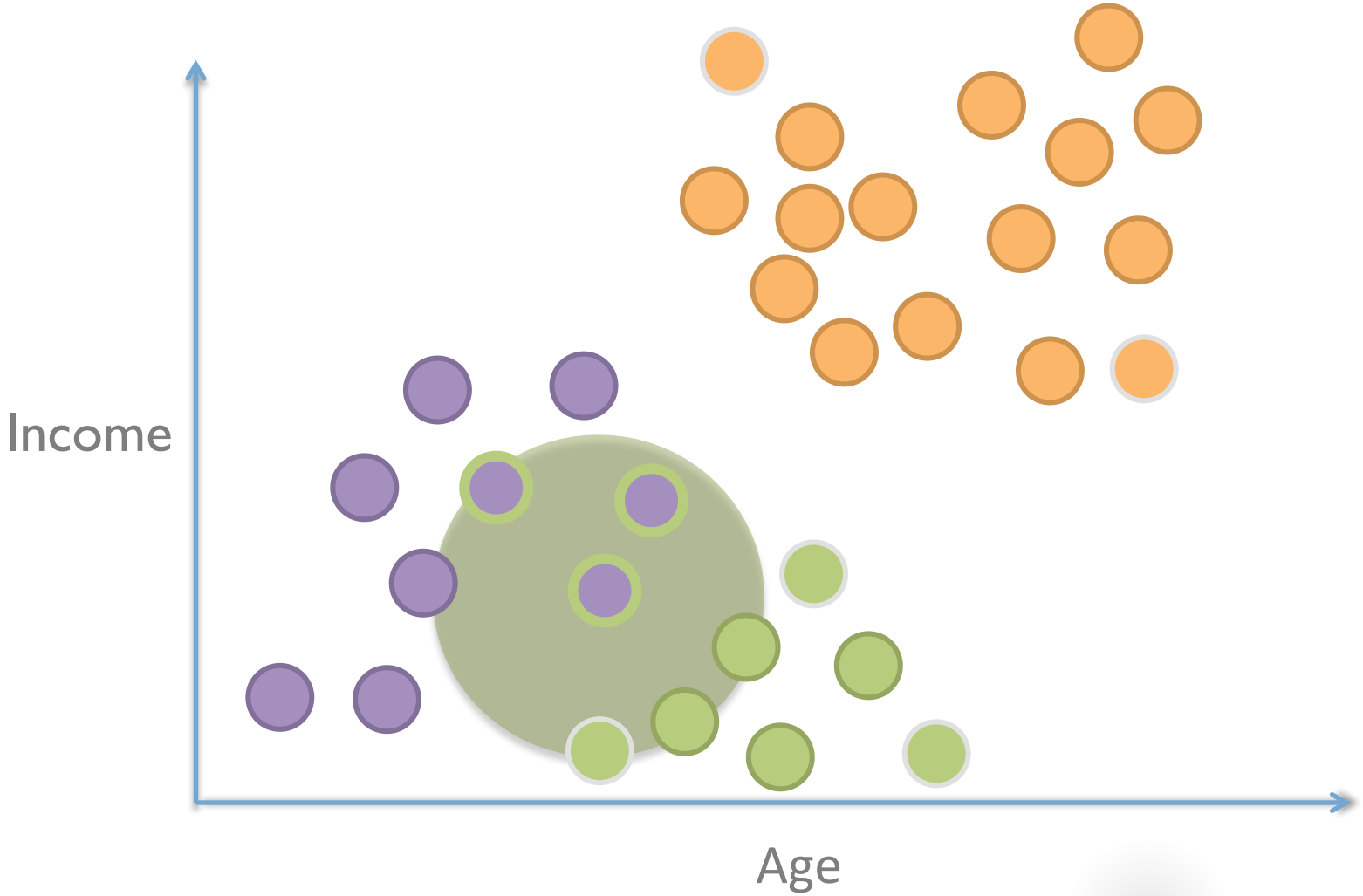

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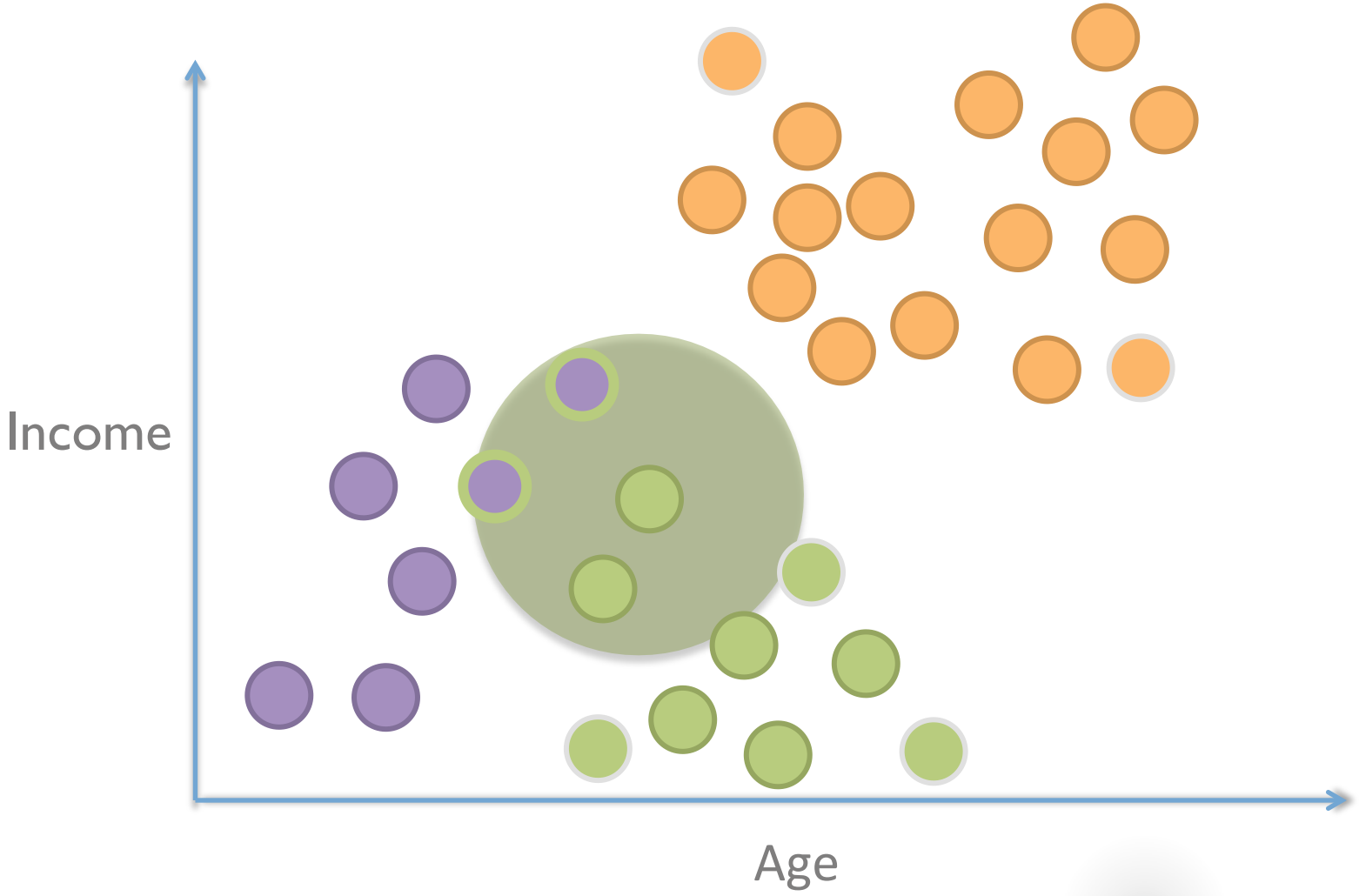

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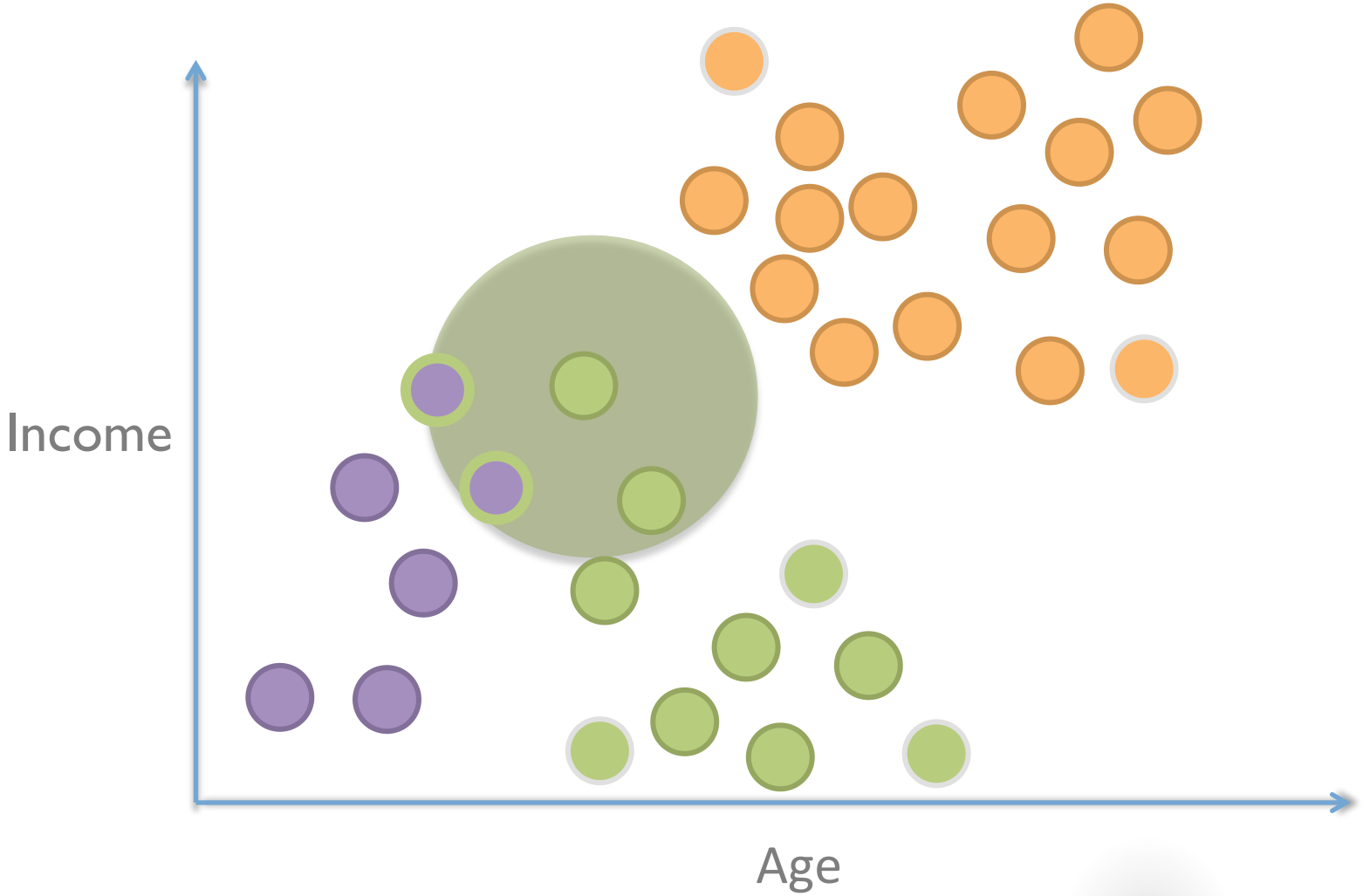
DBSCAN

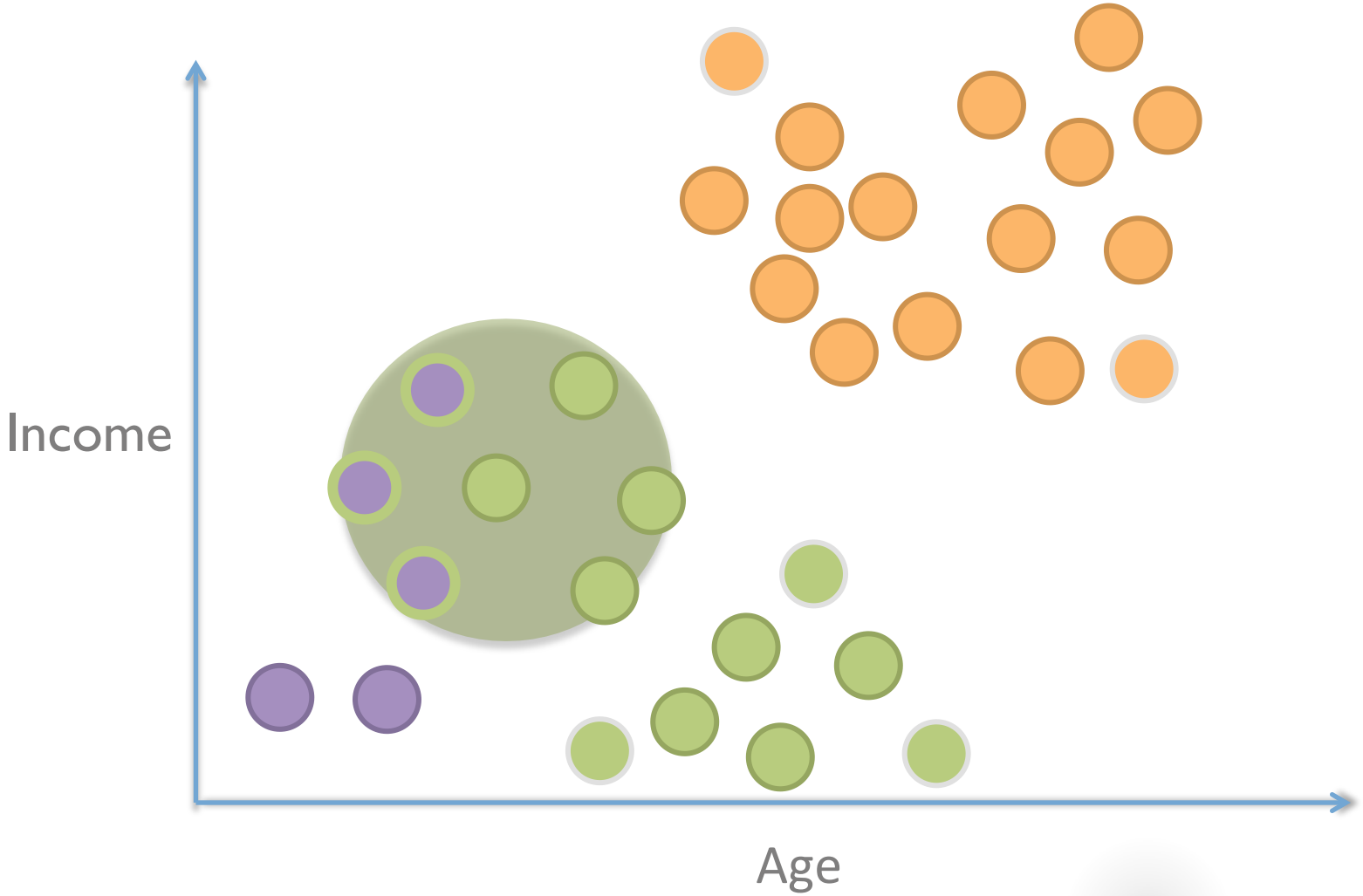
Keep adding neighbors within *epsilon* as chain reaction



epsilon = 1.75
n_clu = 3

DBSCAN

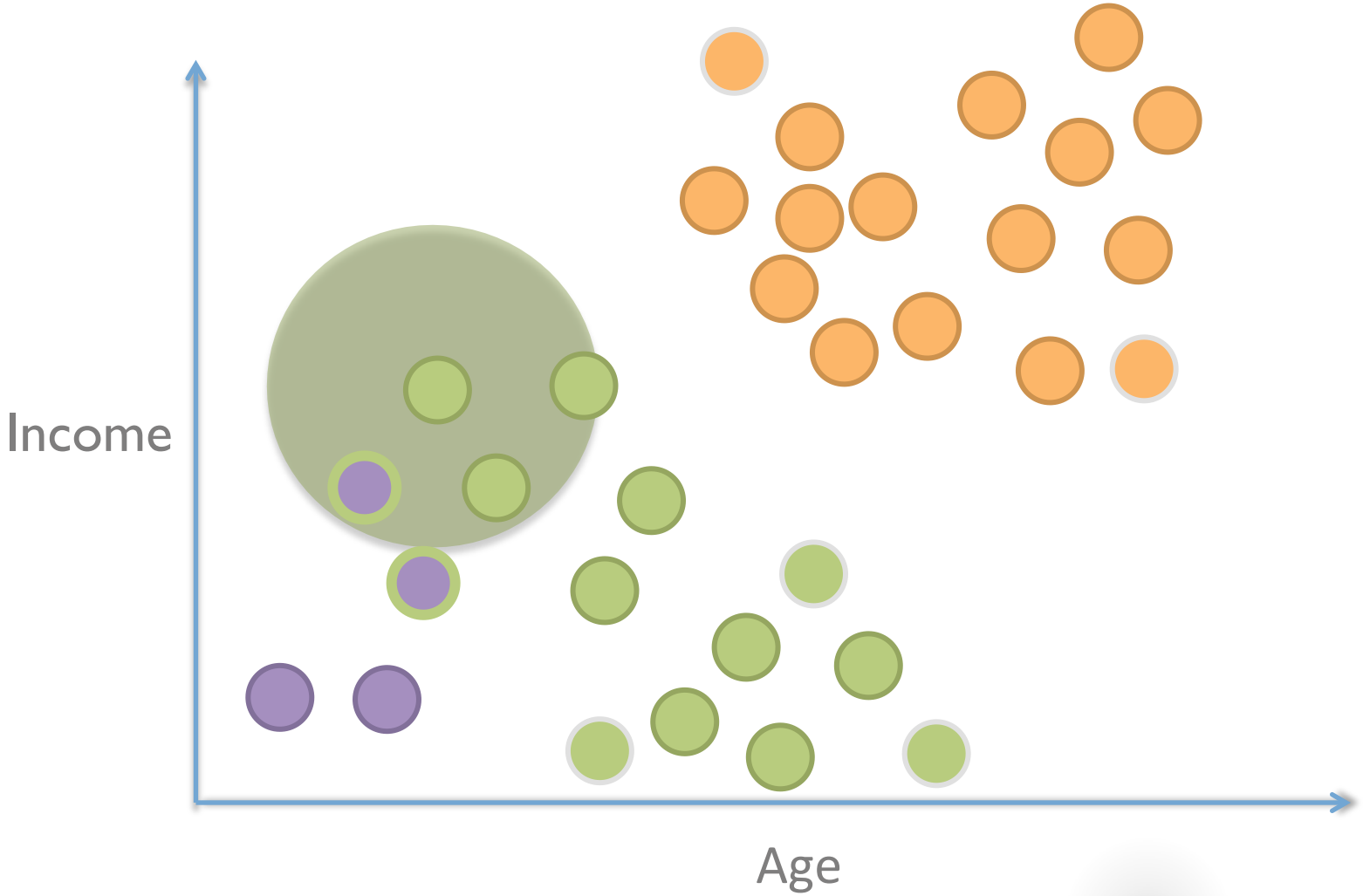
Keep adding neighbors within *epsilon* as chain reaction



epsilon = 1.75
n_clu = 3

DBSCAN

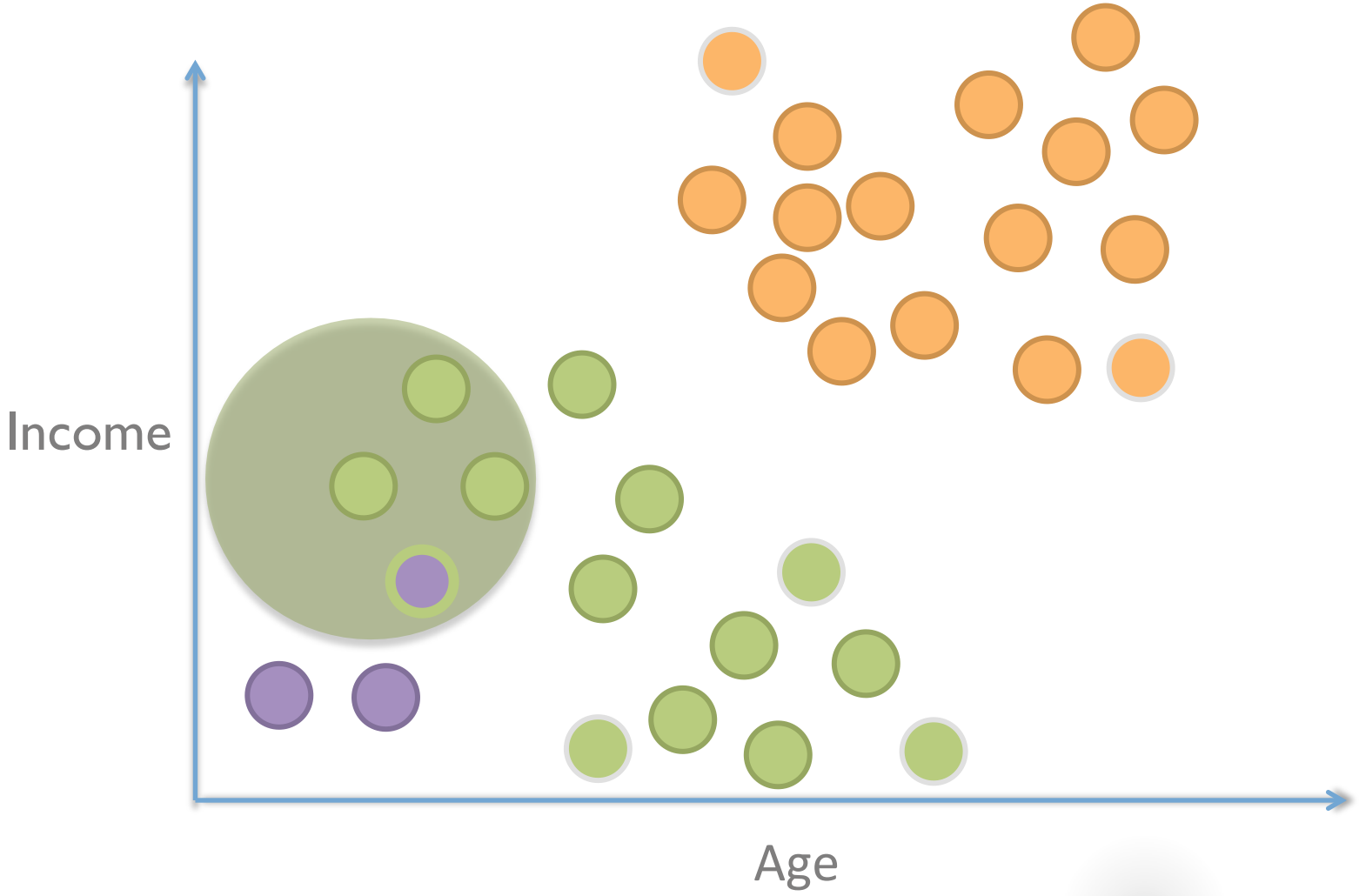
Keep adding neighbors within *epsilon* as chain reaction



epsilon = 1.75
n_clu = 3

DBSCAN

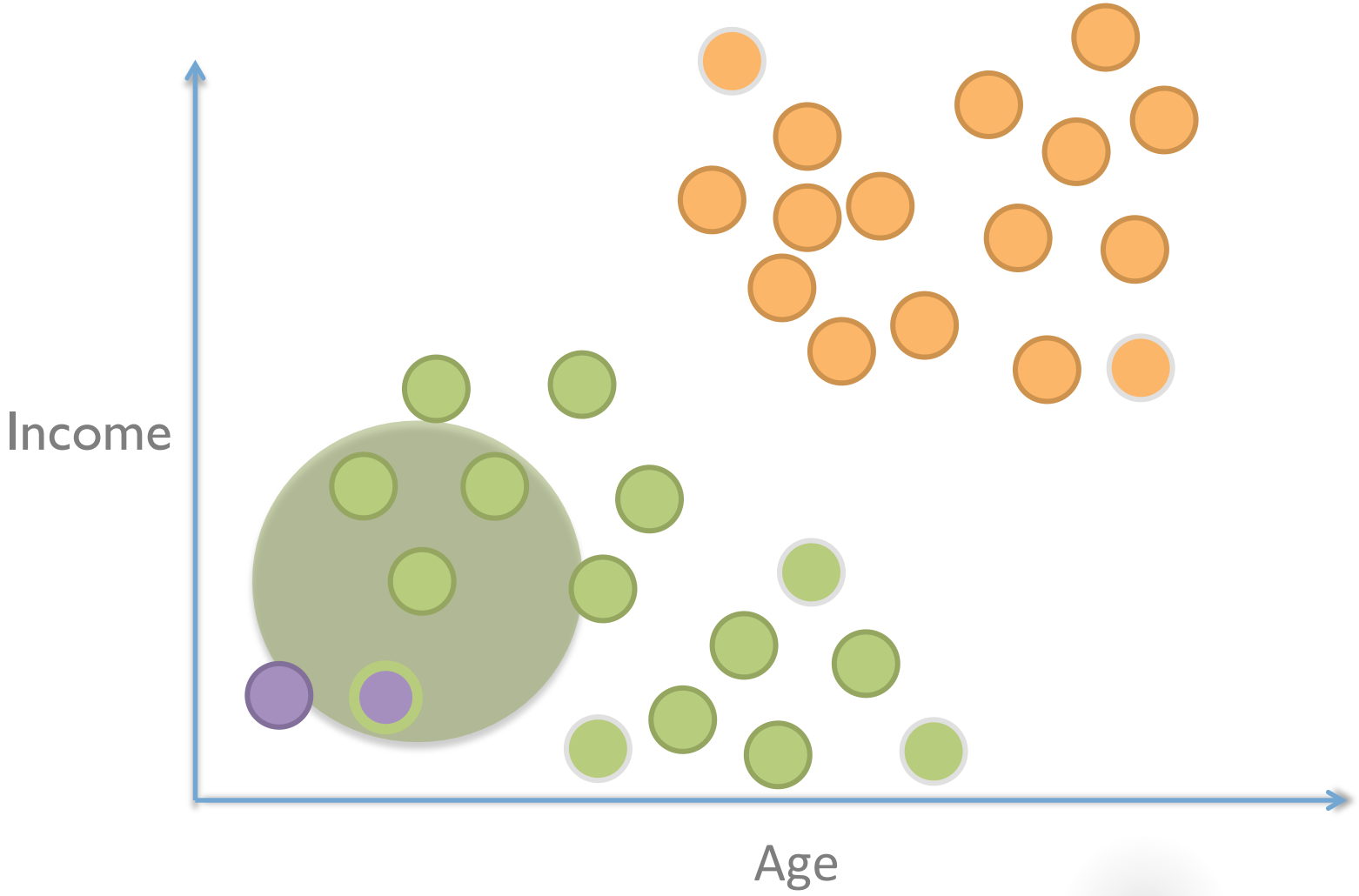
Keep adding neighbors within *epsilon* as chain reaction



epsilon = 1.75
n_clu = 3

DBSCAN

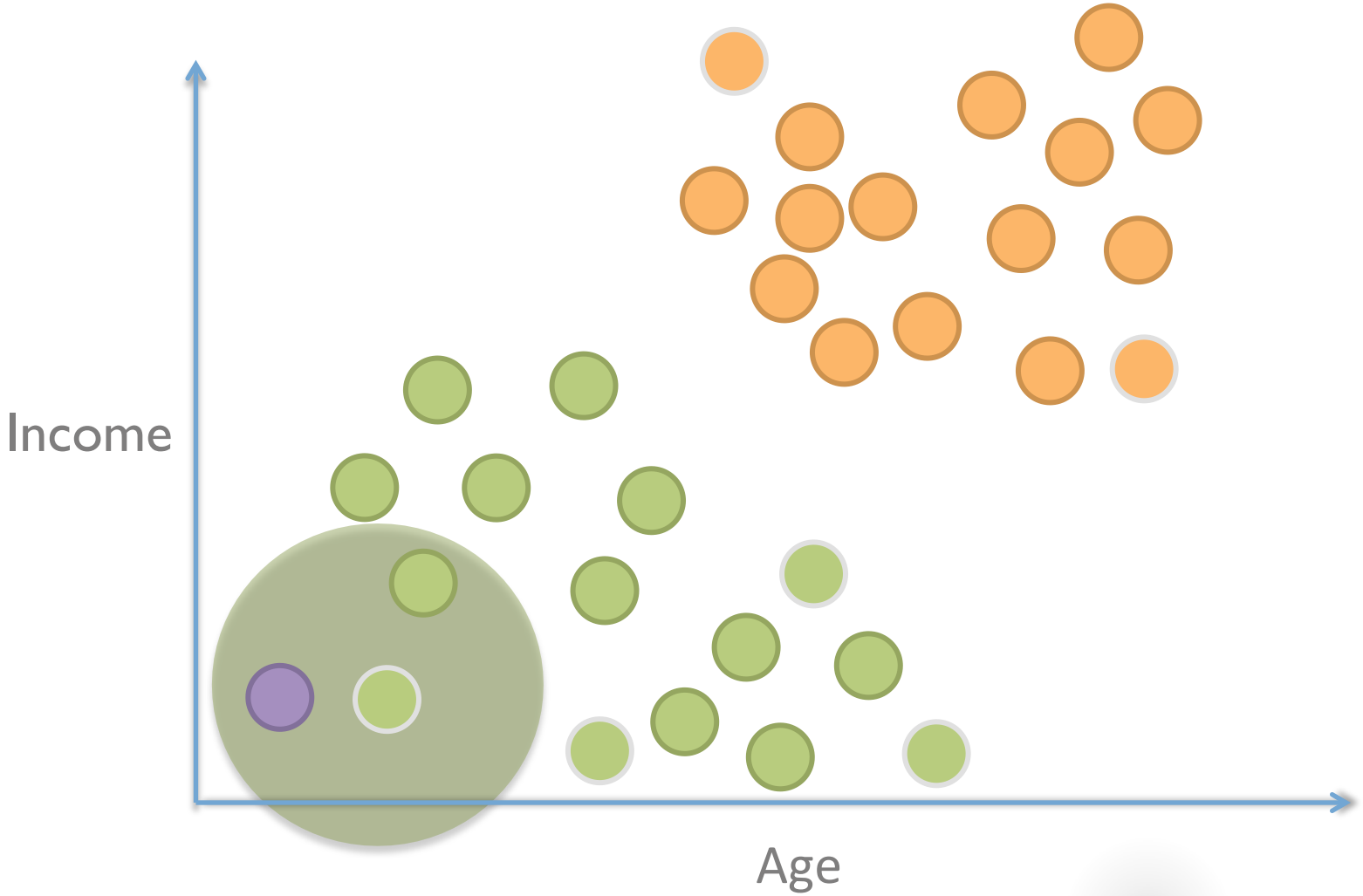
Keep adding neighbors within *epsilon* as chain reaction



epsilon = 1.75
n_clu = 3

DBSCAN

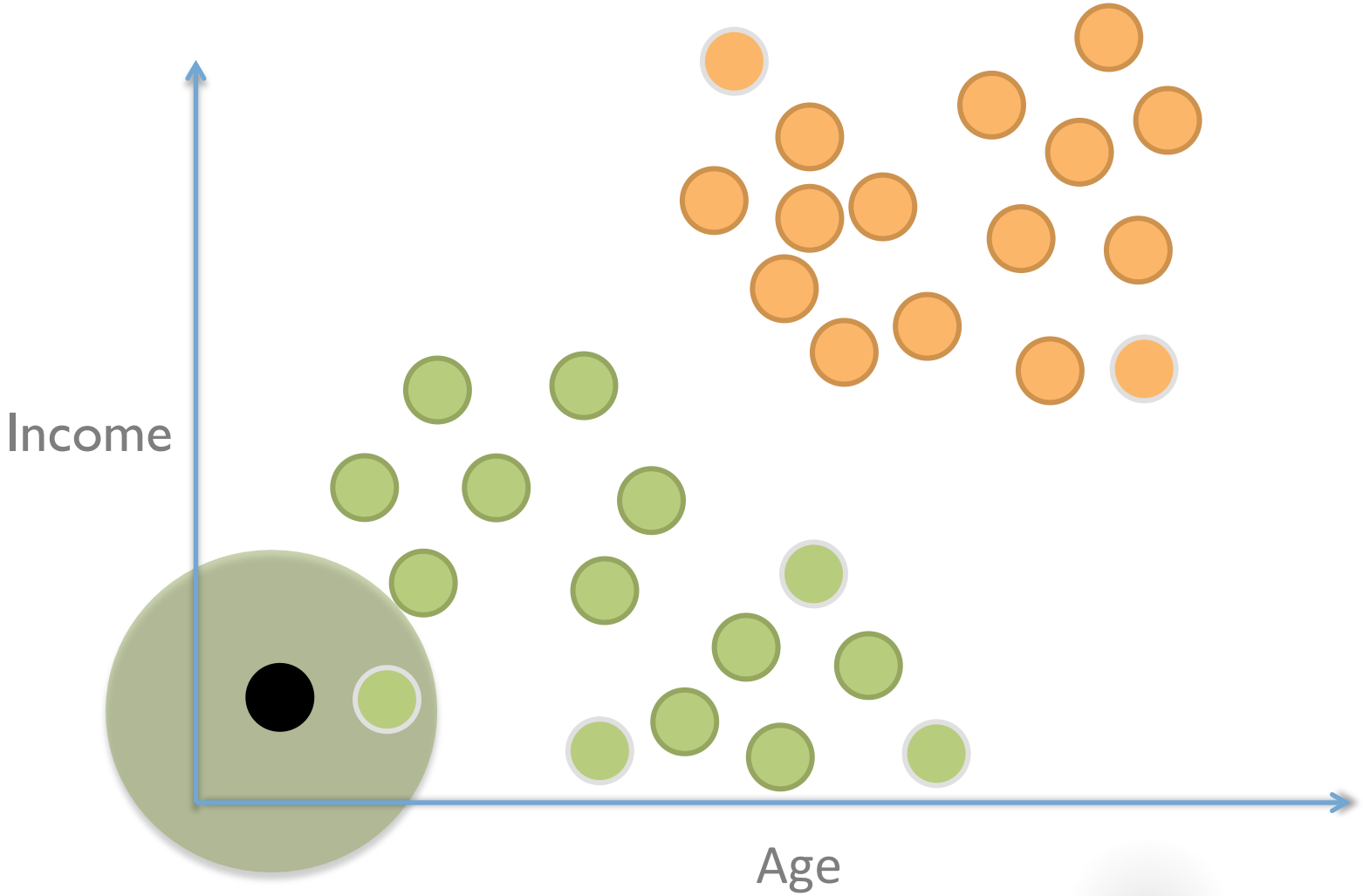
Keep adding neighbors within *epsilon* as chain reaction



epsilon = 1.75
n_clu = 3

DBSCAN

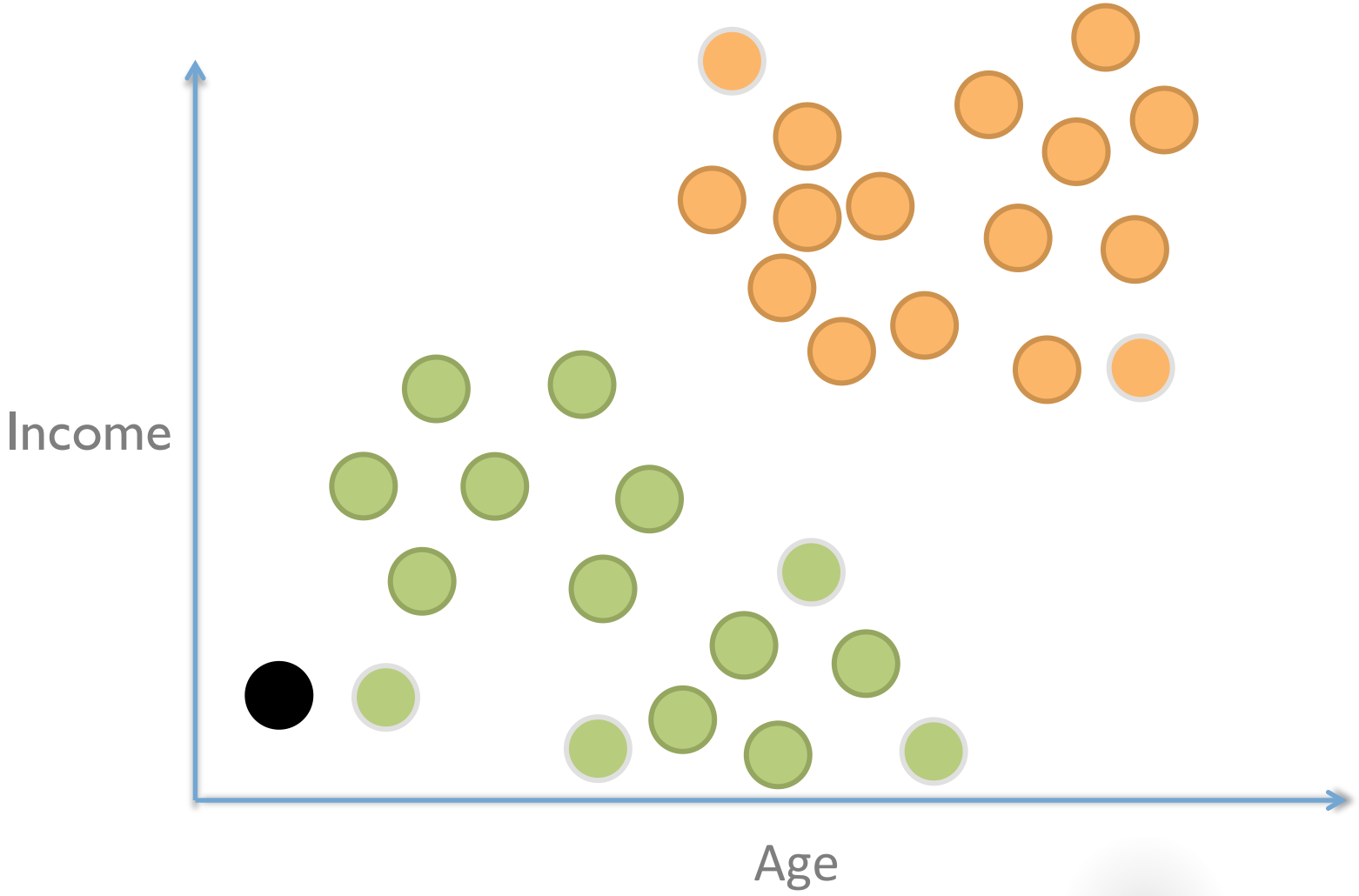
If there is a point that does not have *n_clu* neighbors and is not reached from a core point: It is a **noise** point.



epsilon = 1.75
n_clu = 3

DBSCAN

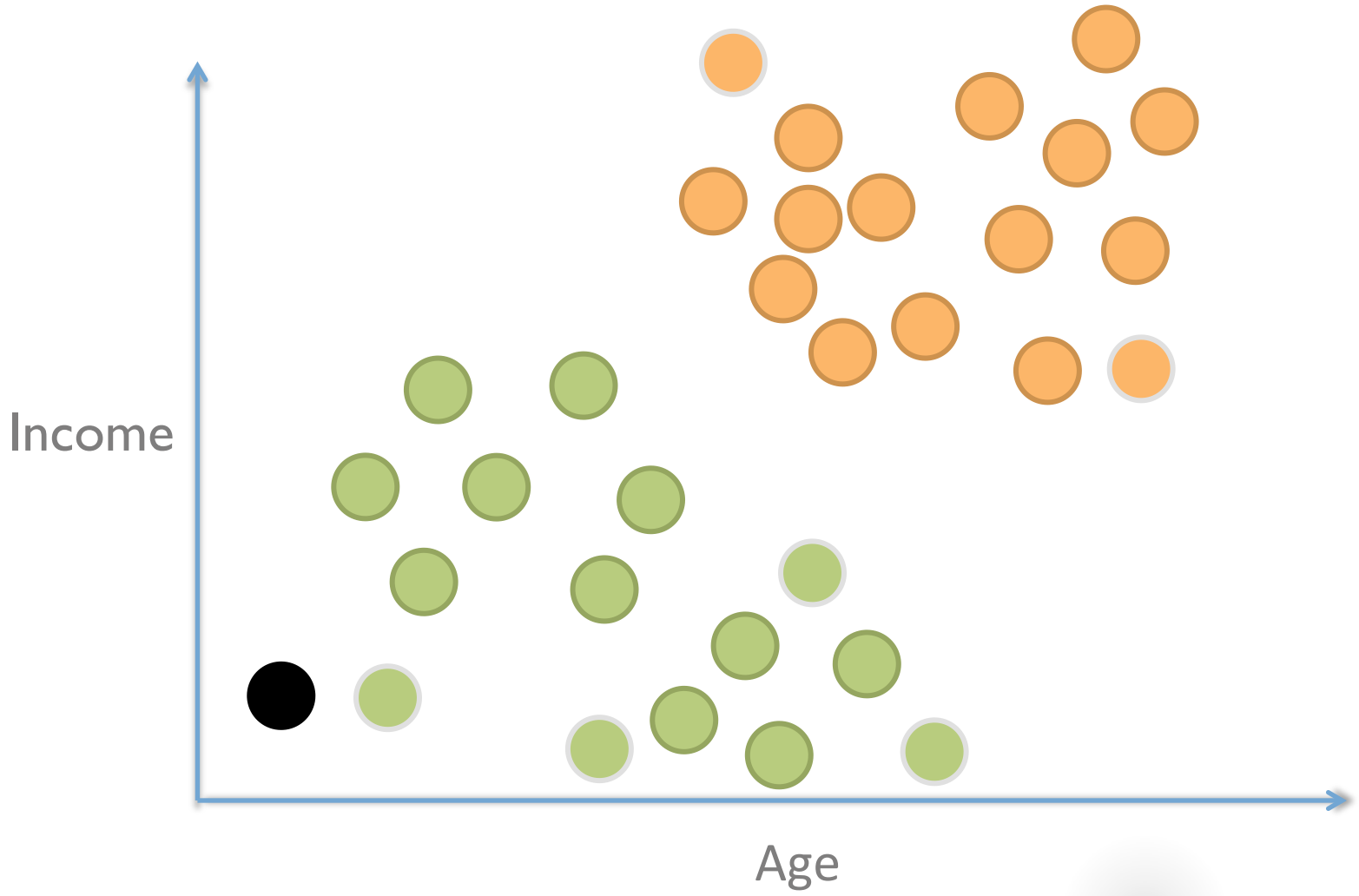
Ta--daa! Notice the core points, density-reachable points (at the borders) and the **noise** point.



epsilon = 1.75
n_clu = 3

DBSCAN

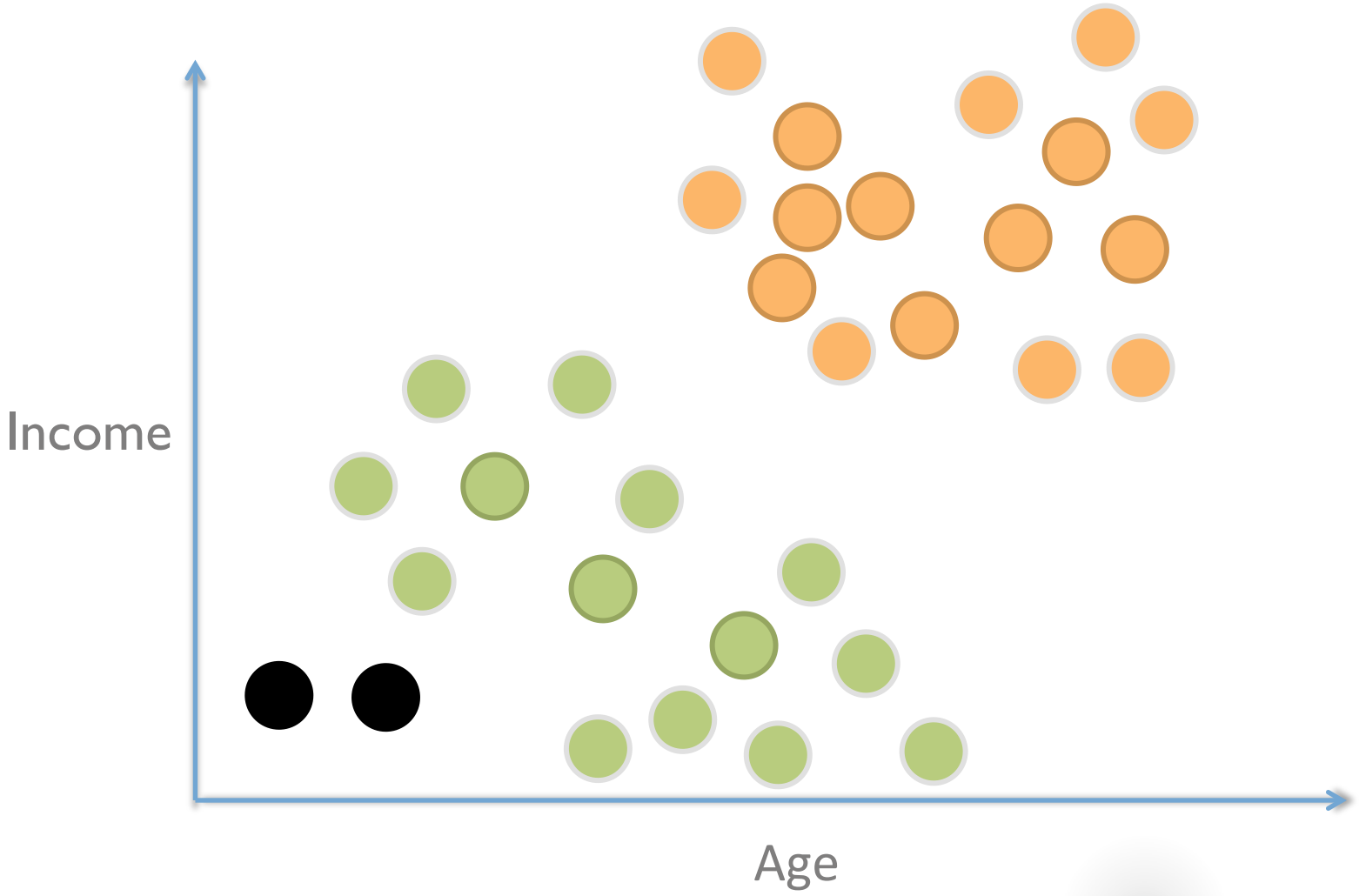
The effect of the parameters



epsilon = 1.75
n_clu = 5

DBSCAN

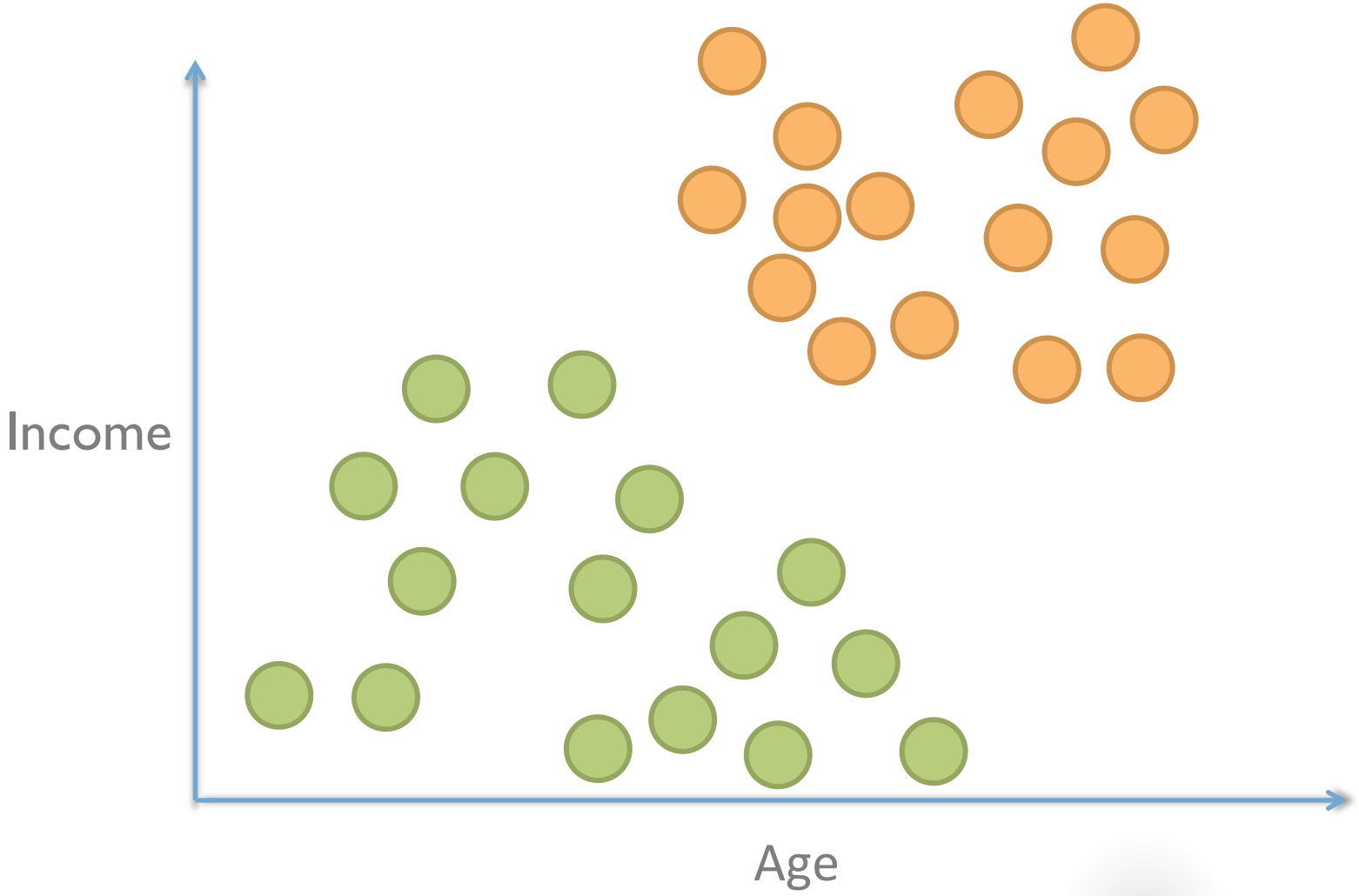
The effect of the parameters



epsilon = 1.75
n_clu = 1

DBSCAN

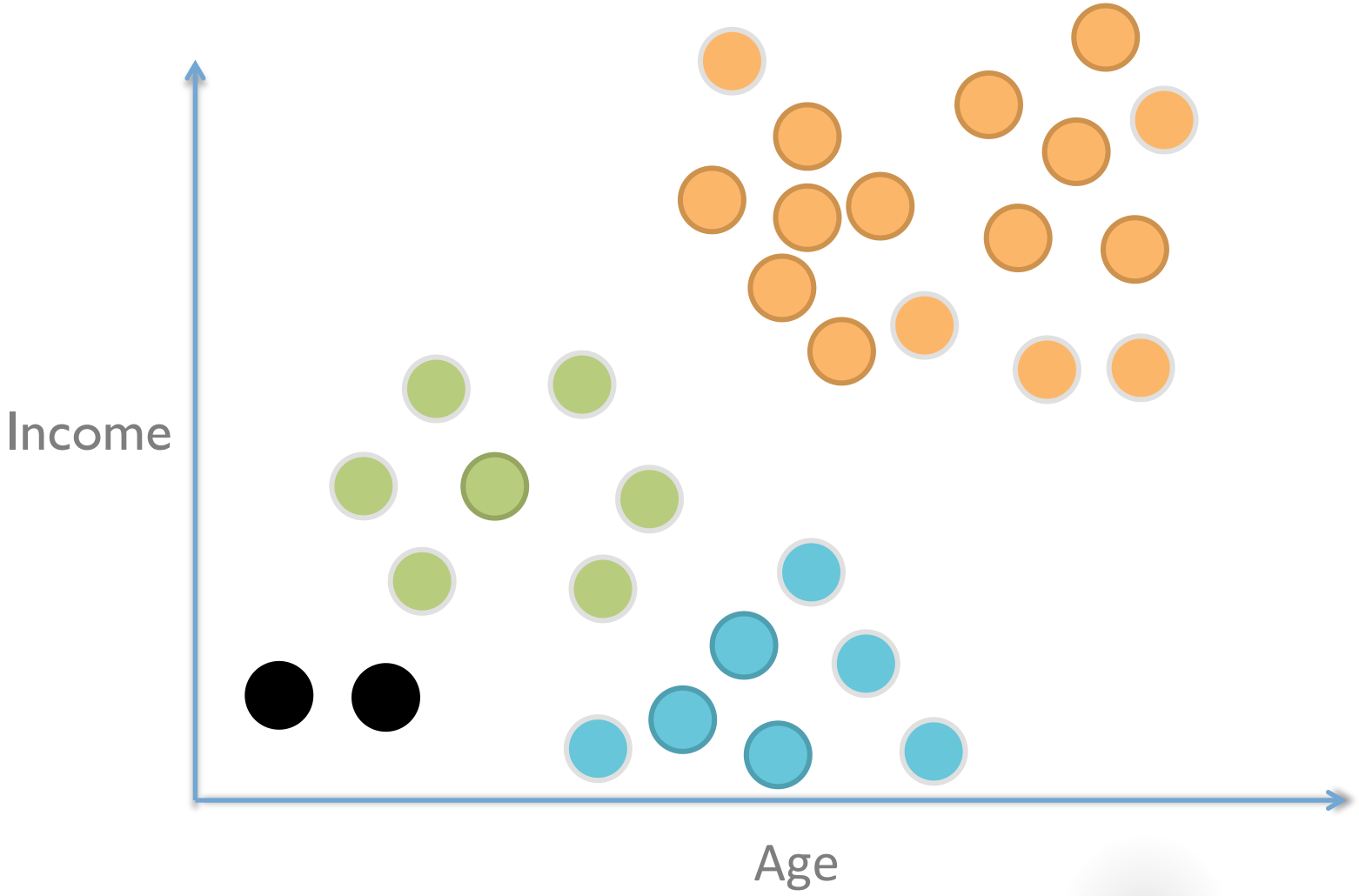
The effect of the parameters



epsilon = 1.25
n_clu = 3

DBSCAN

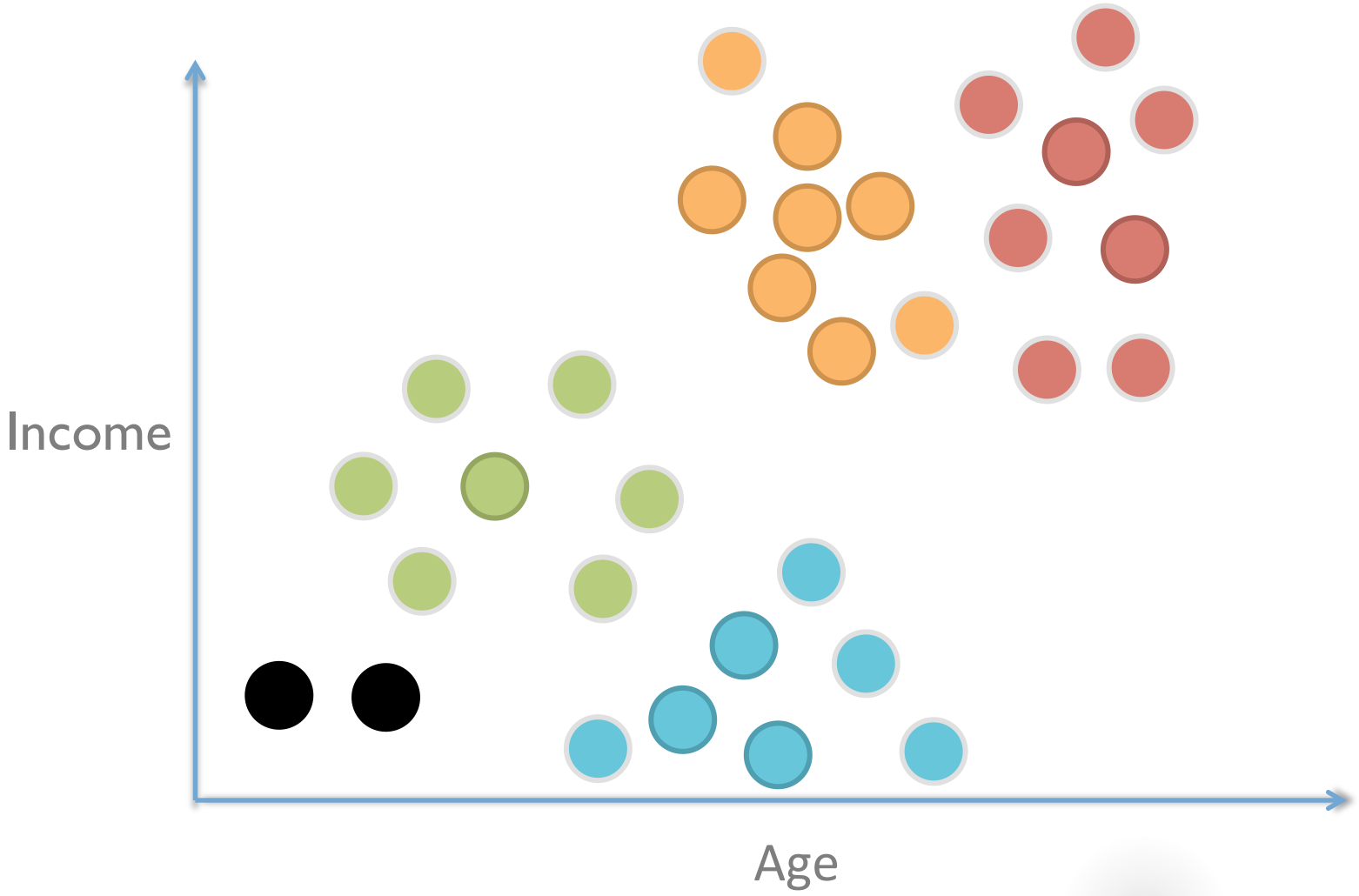
The effect of the parameters



epsilon = 1.00
n_clu = 3

DBSCAN

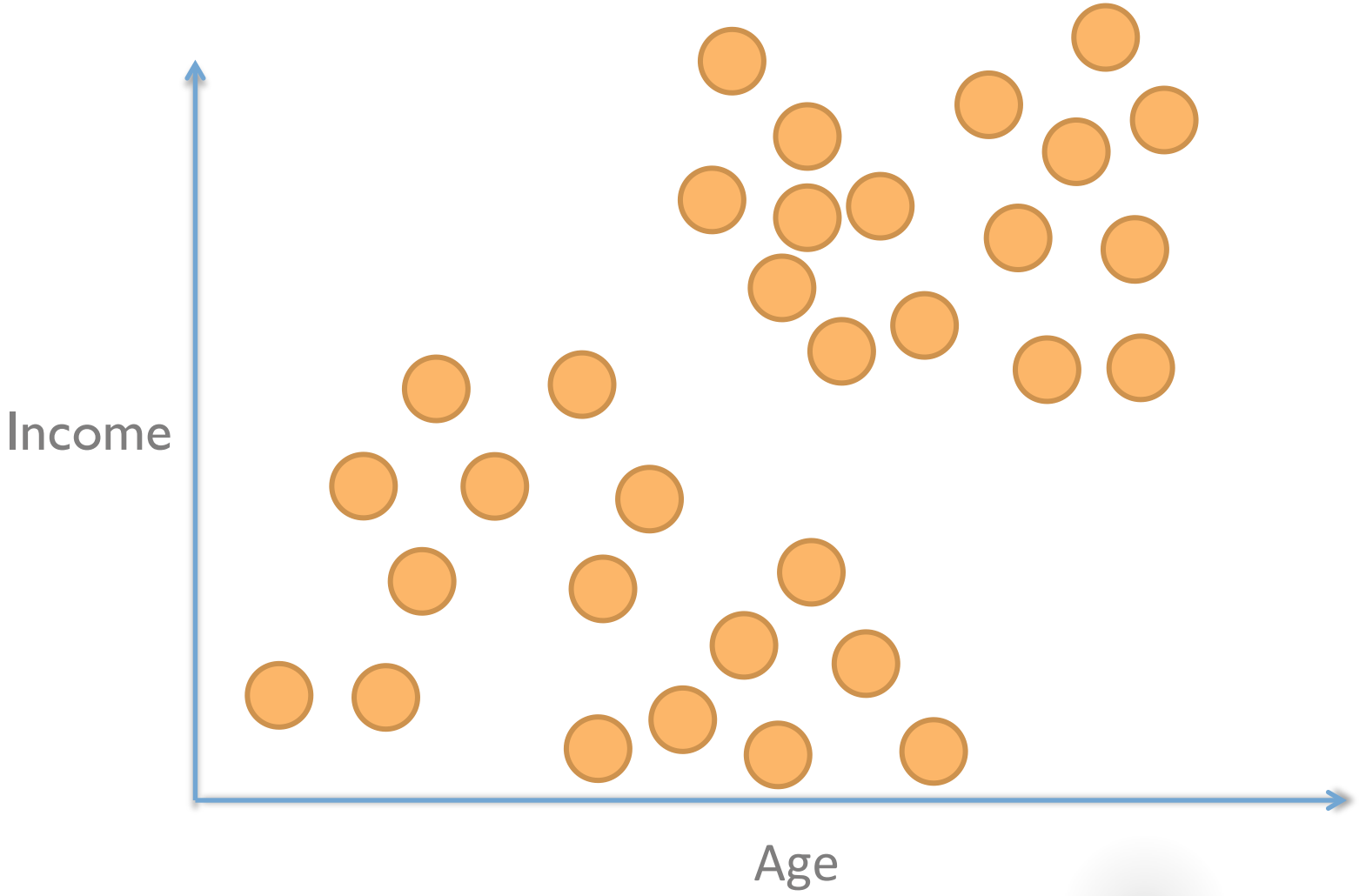
The effect of the parameters



epsilon = 3.50
n_clu = 3

DBSCAN

The effect of the parameters

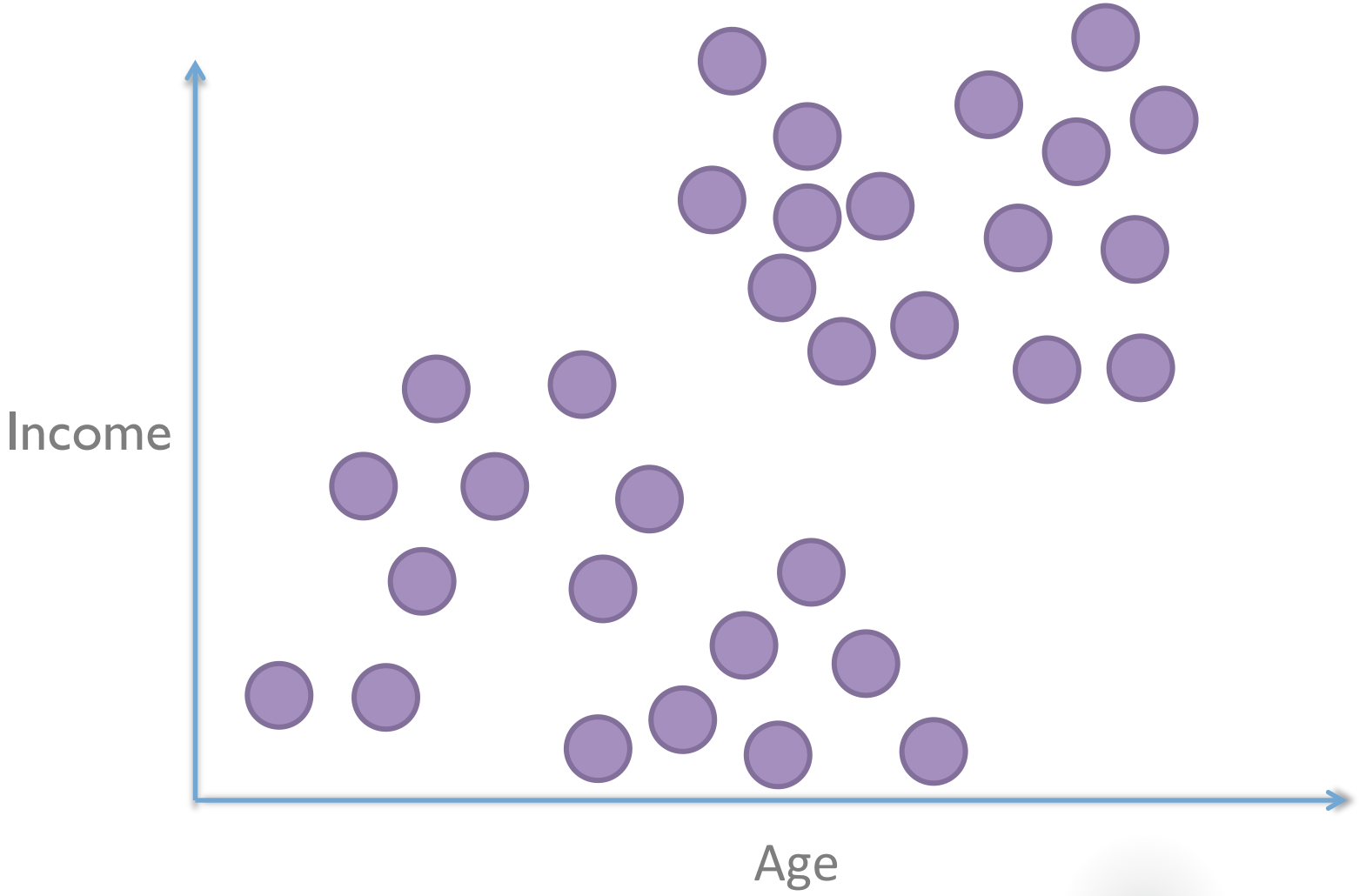


```
from sklearn.cluster import DBSCAN
```

```
DBSCAN( eps = 0.5, min_samples = 5, metric =“euclidean” )
```

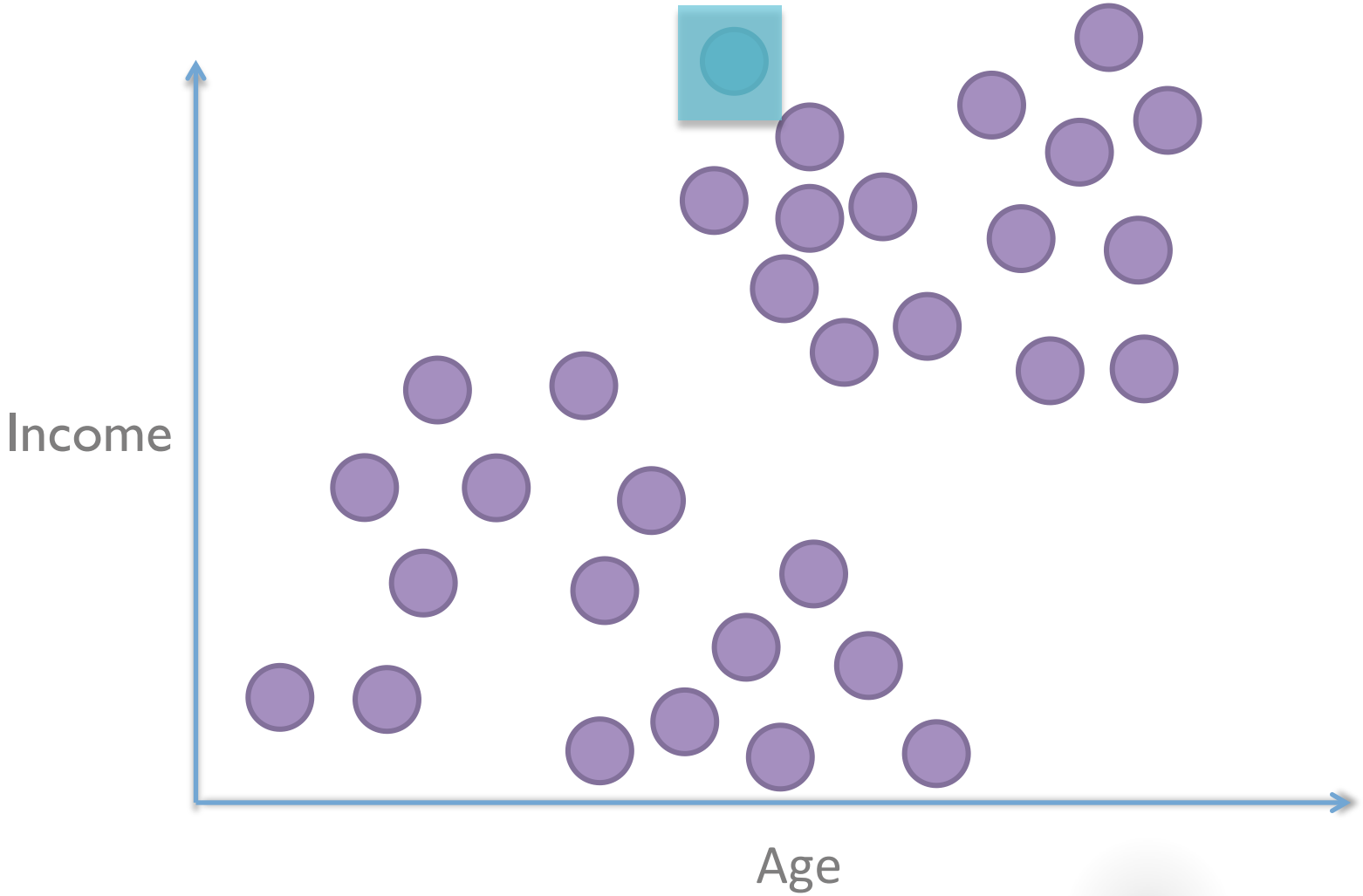
Mean Shift

Mean Shift



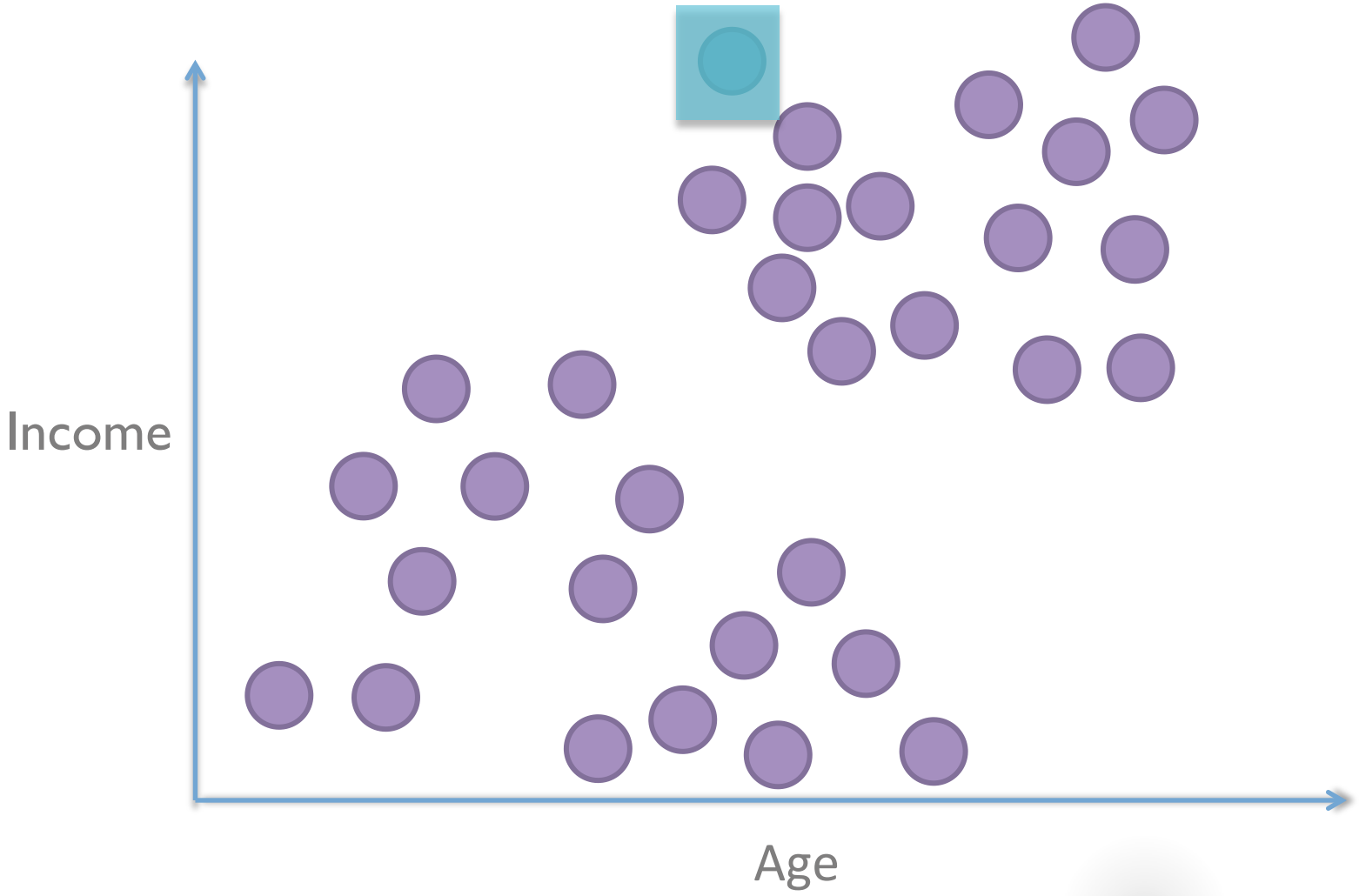
Mean Shift

Start with a centroid at a point



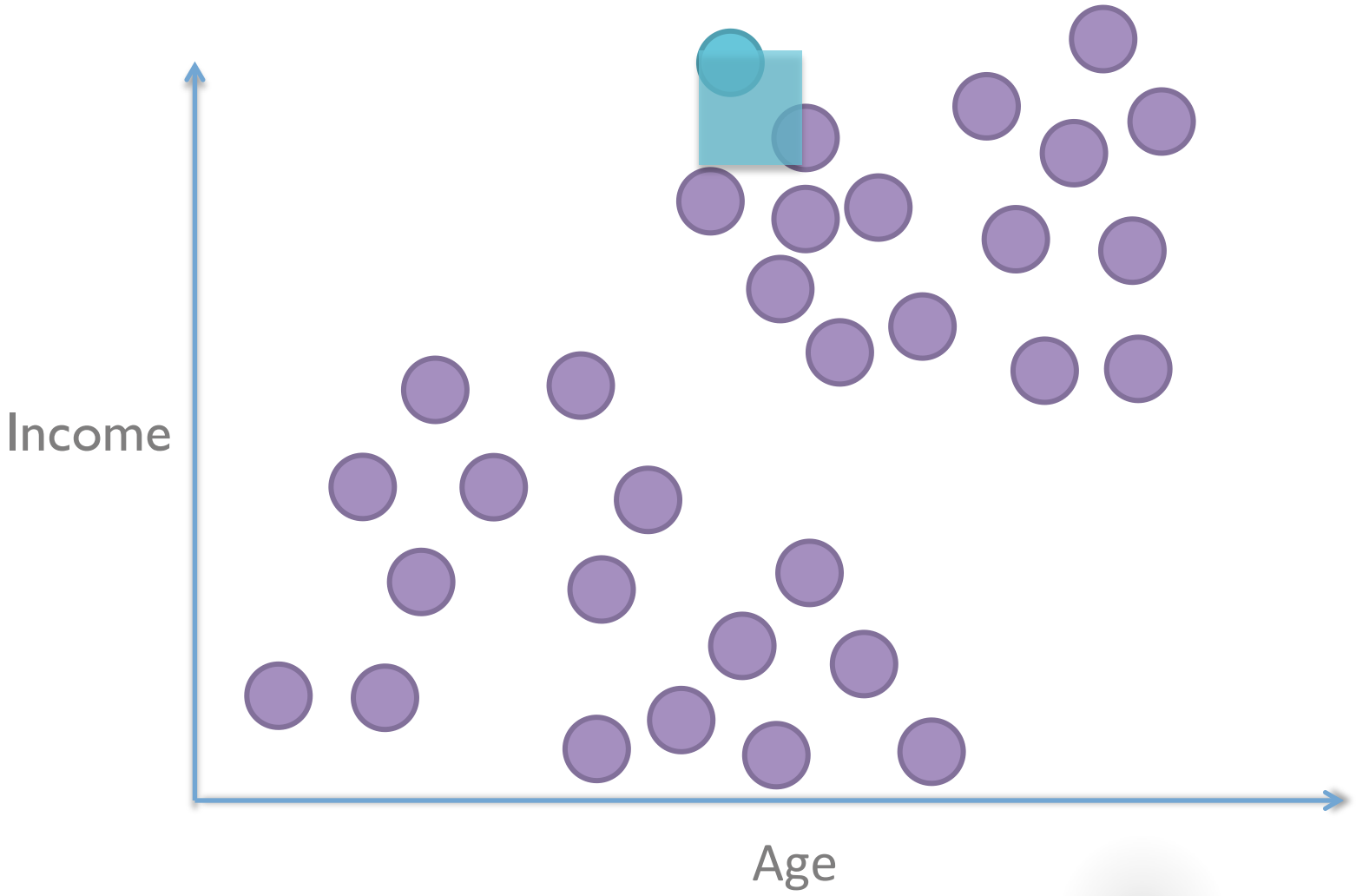
Mean Shift

Sample local density, follow gradient towards denser direction



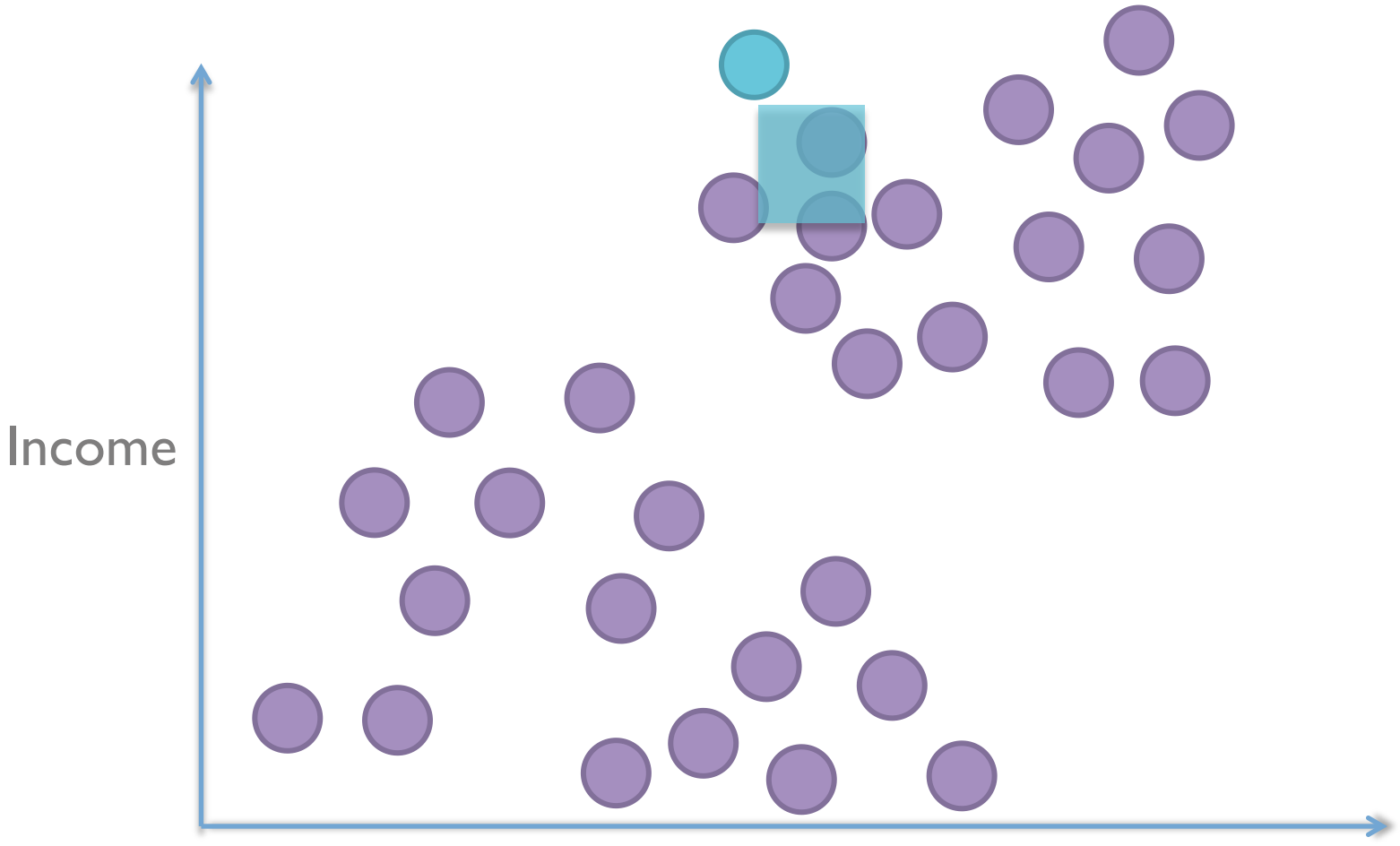
Mean Shift

Sample local density, follow gradient towards denser direction



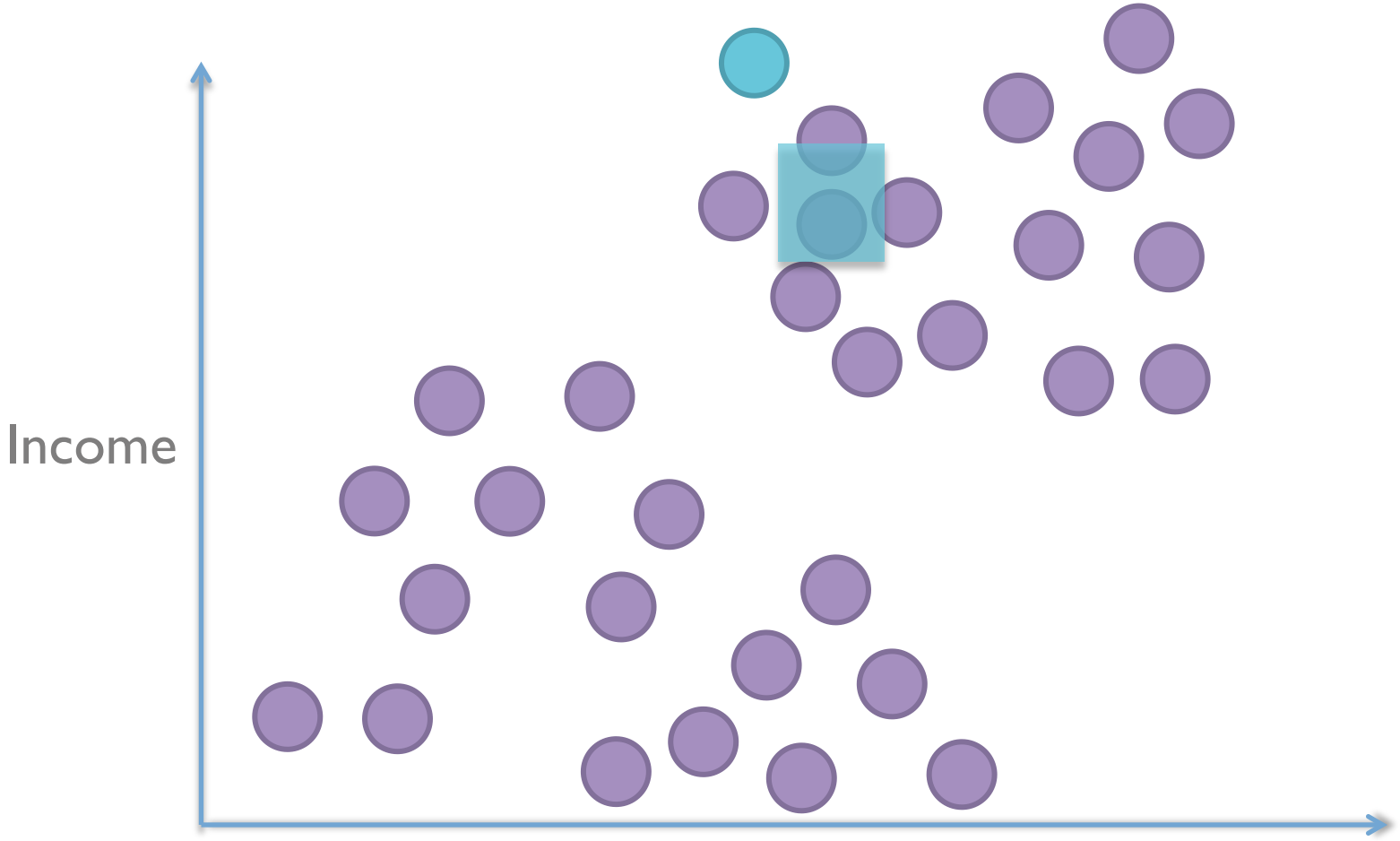
Mean Shift

Sample local density, follow gradient towards denser direction



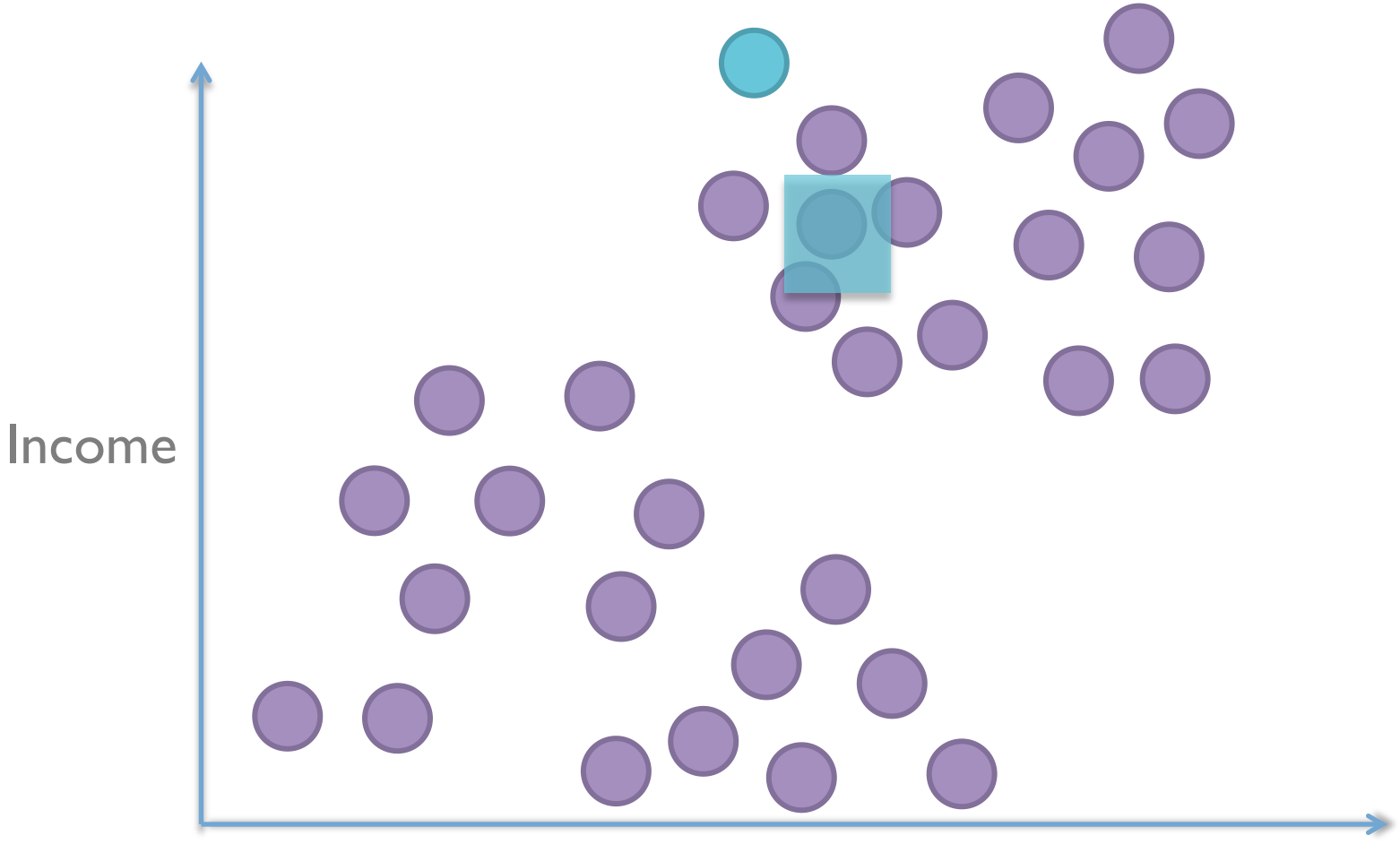
Mean Shift

Sample local density, follow gradient towards denser direction



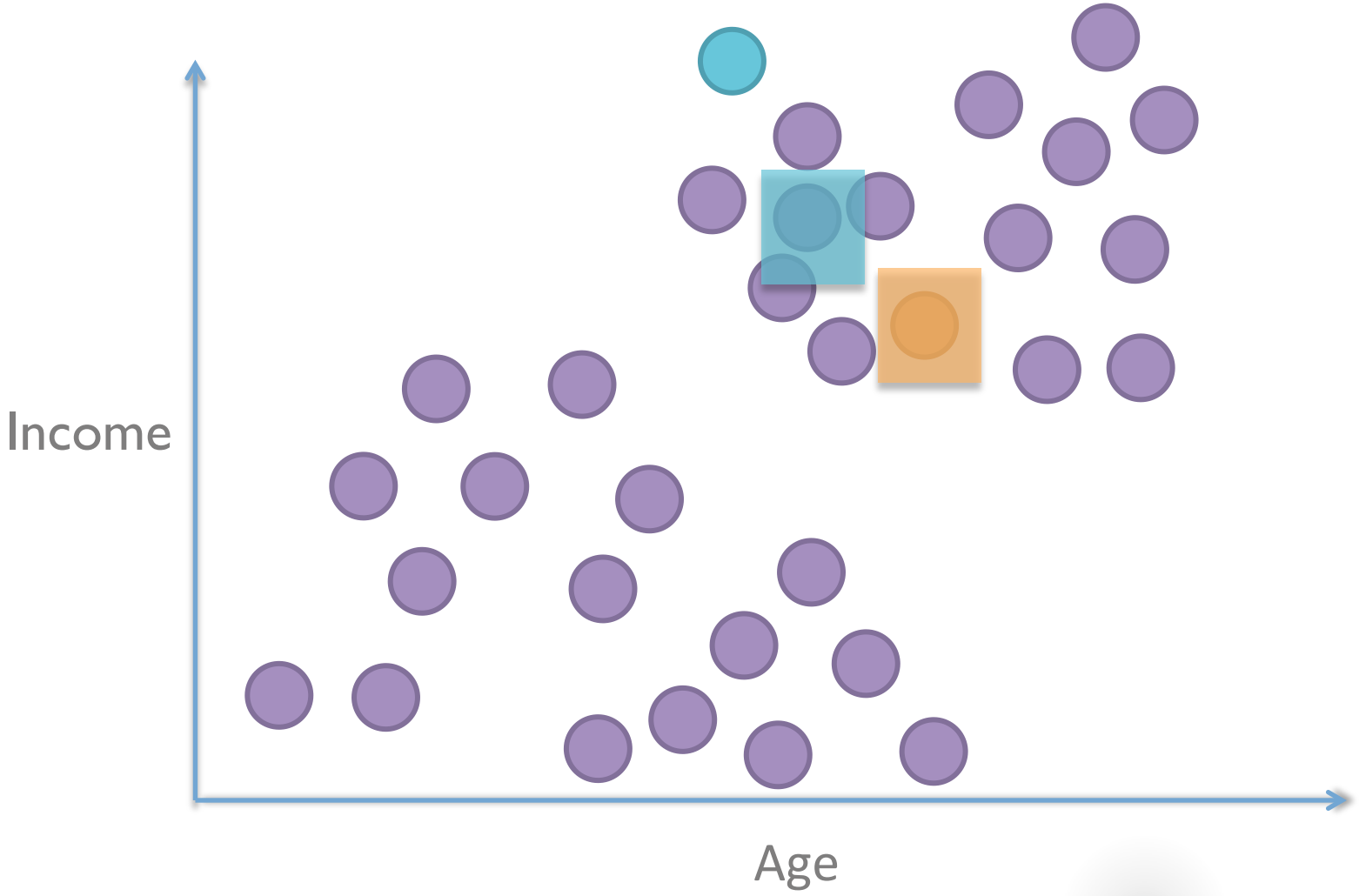
Mean Shift

Found local density maximum! Stop.



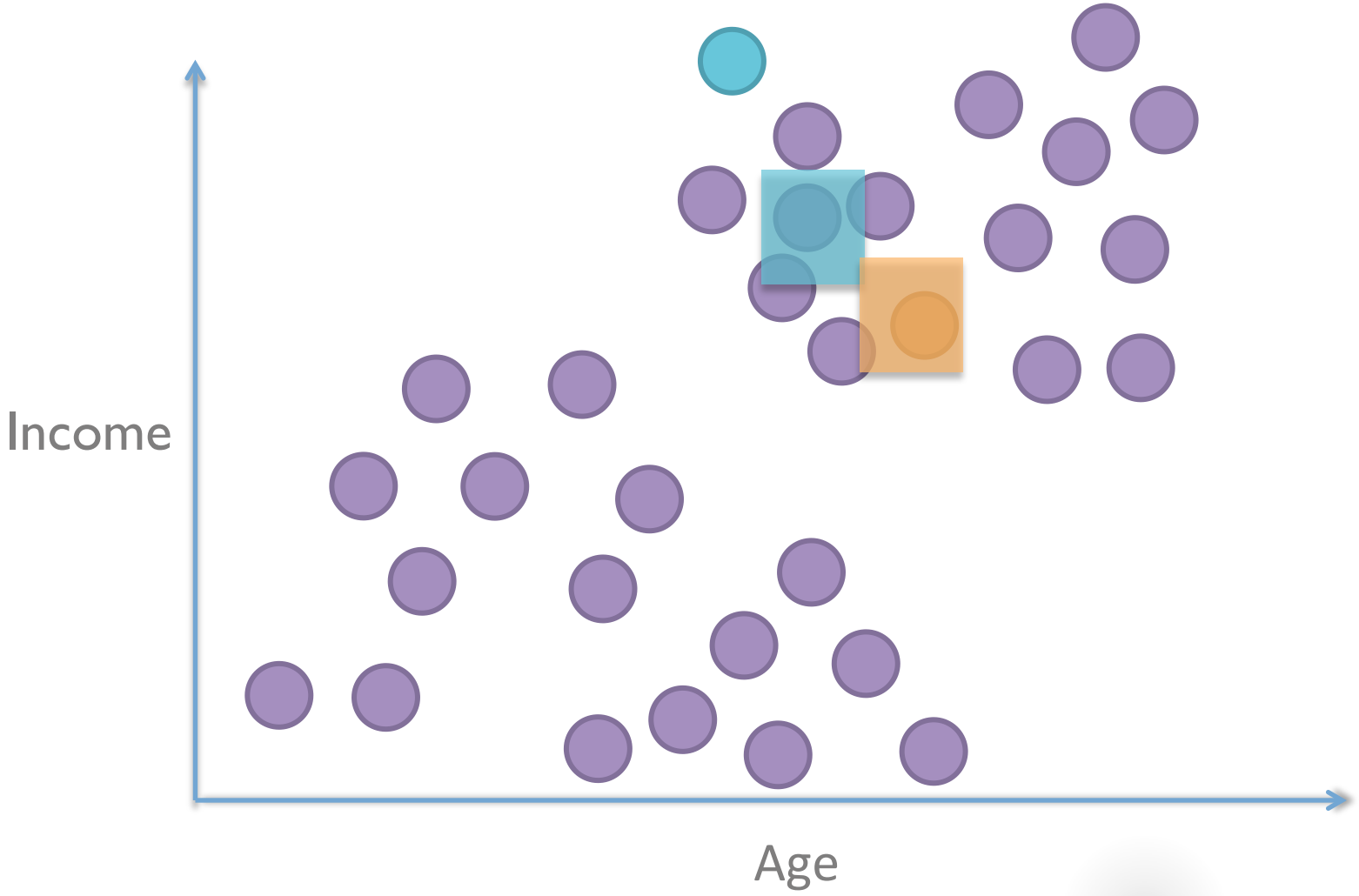
Mean Shift

Start at another point.



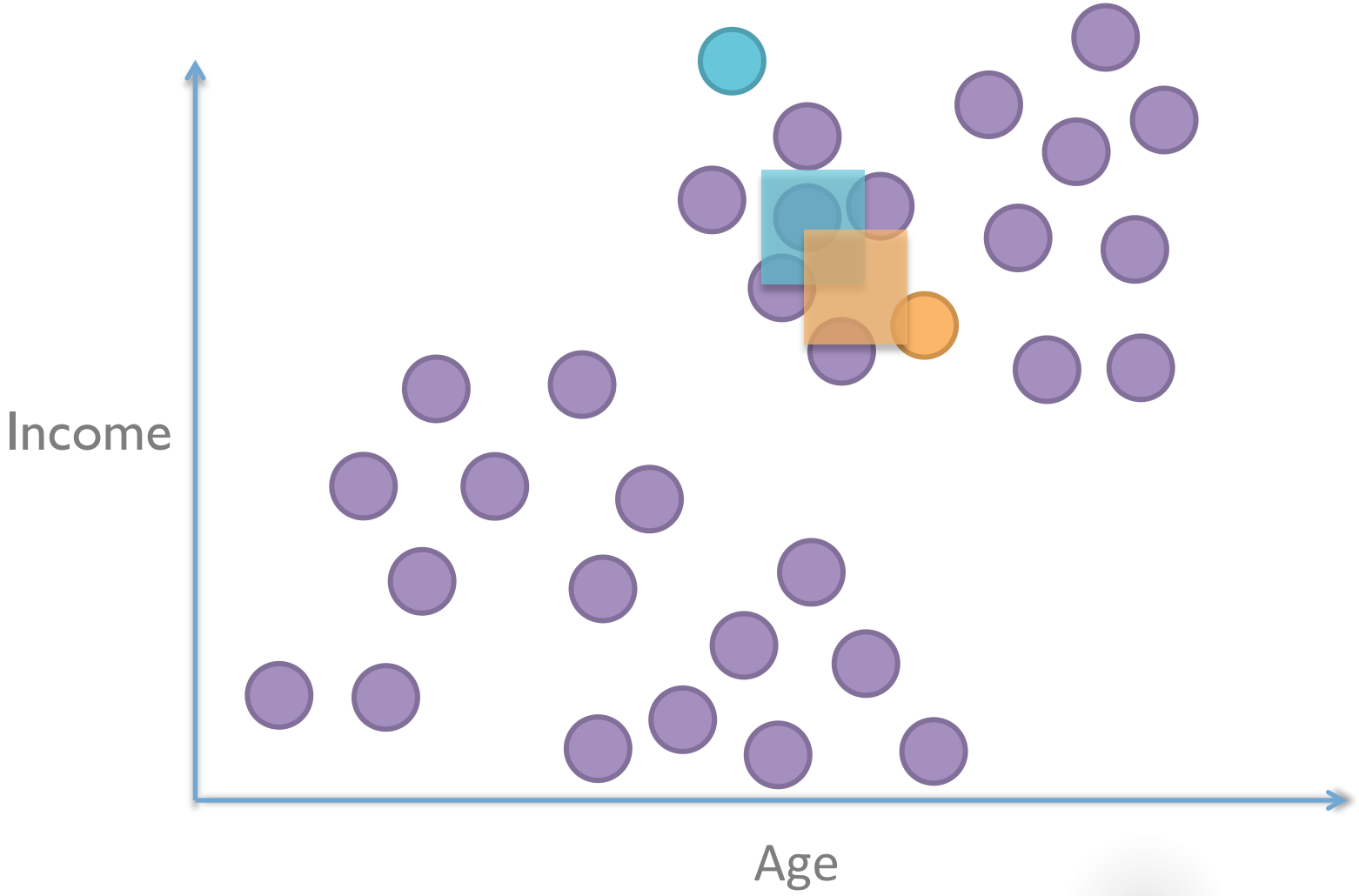
Mean Shift

Sample local density, follow gradient towards denser direction



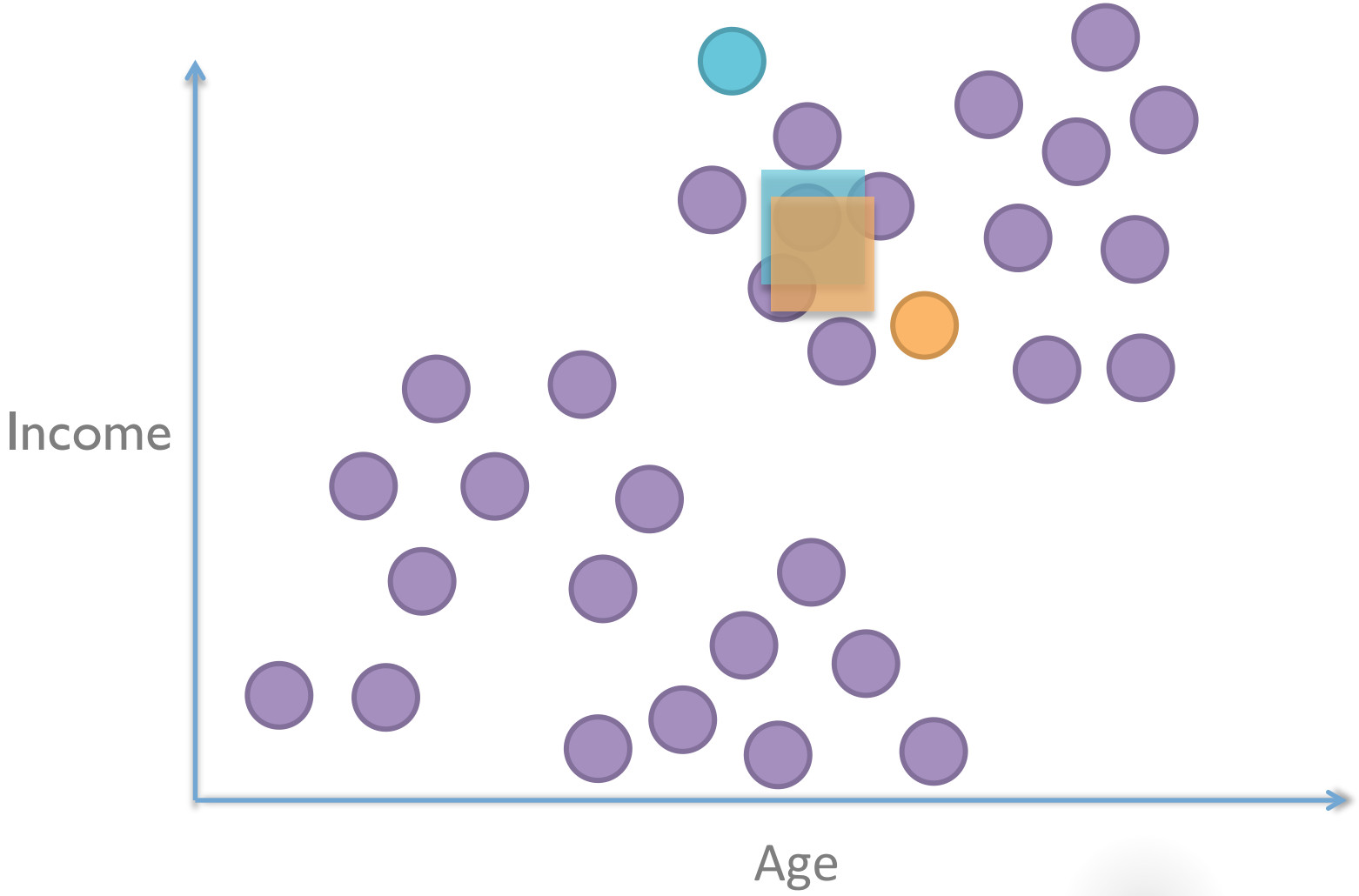
Mean Shift

Sample local density, follow gradient towards denser direction



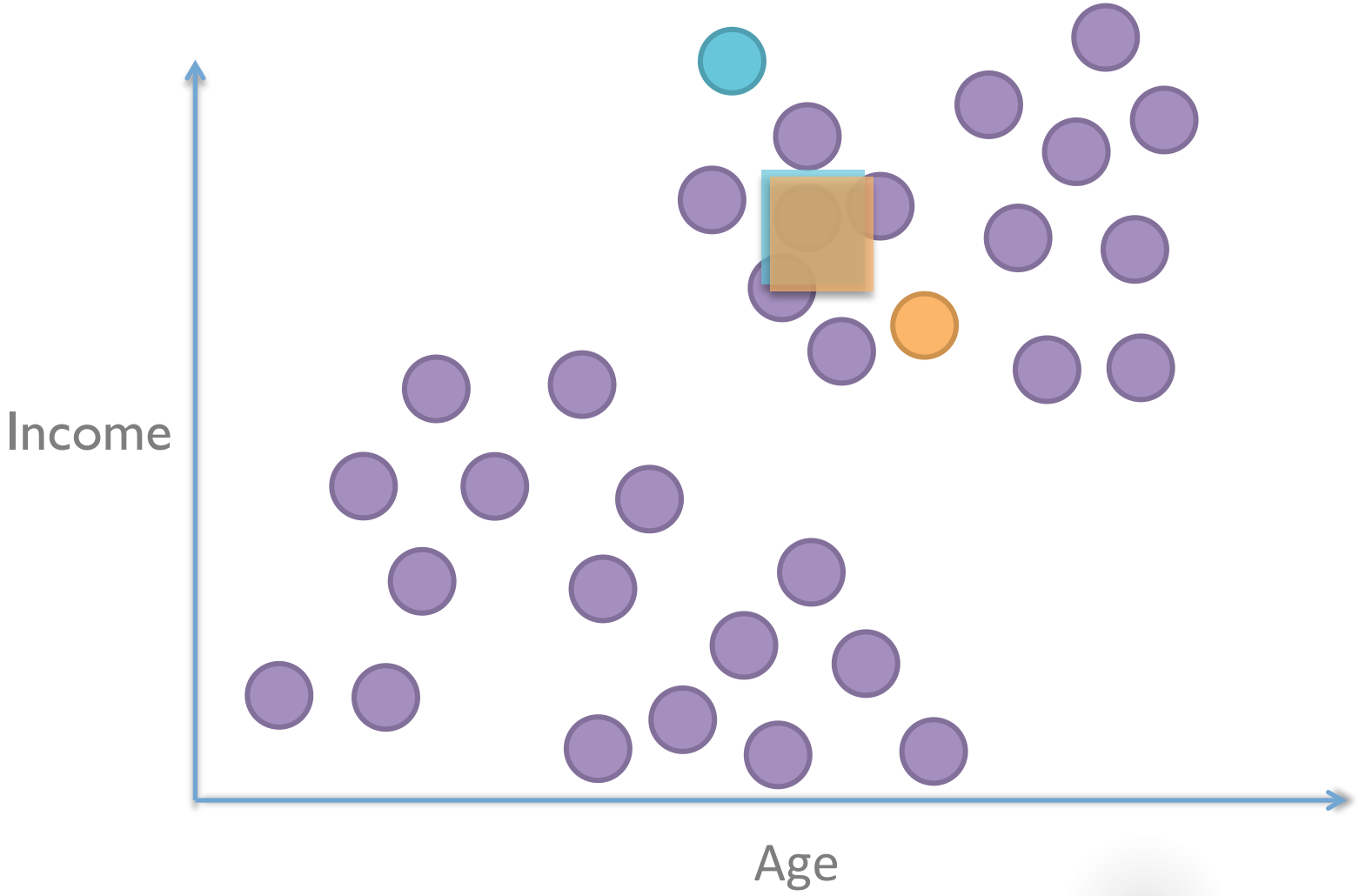
Mean Shift

Sample local density, follow gradient towards denser direction



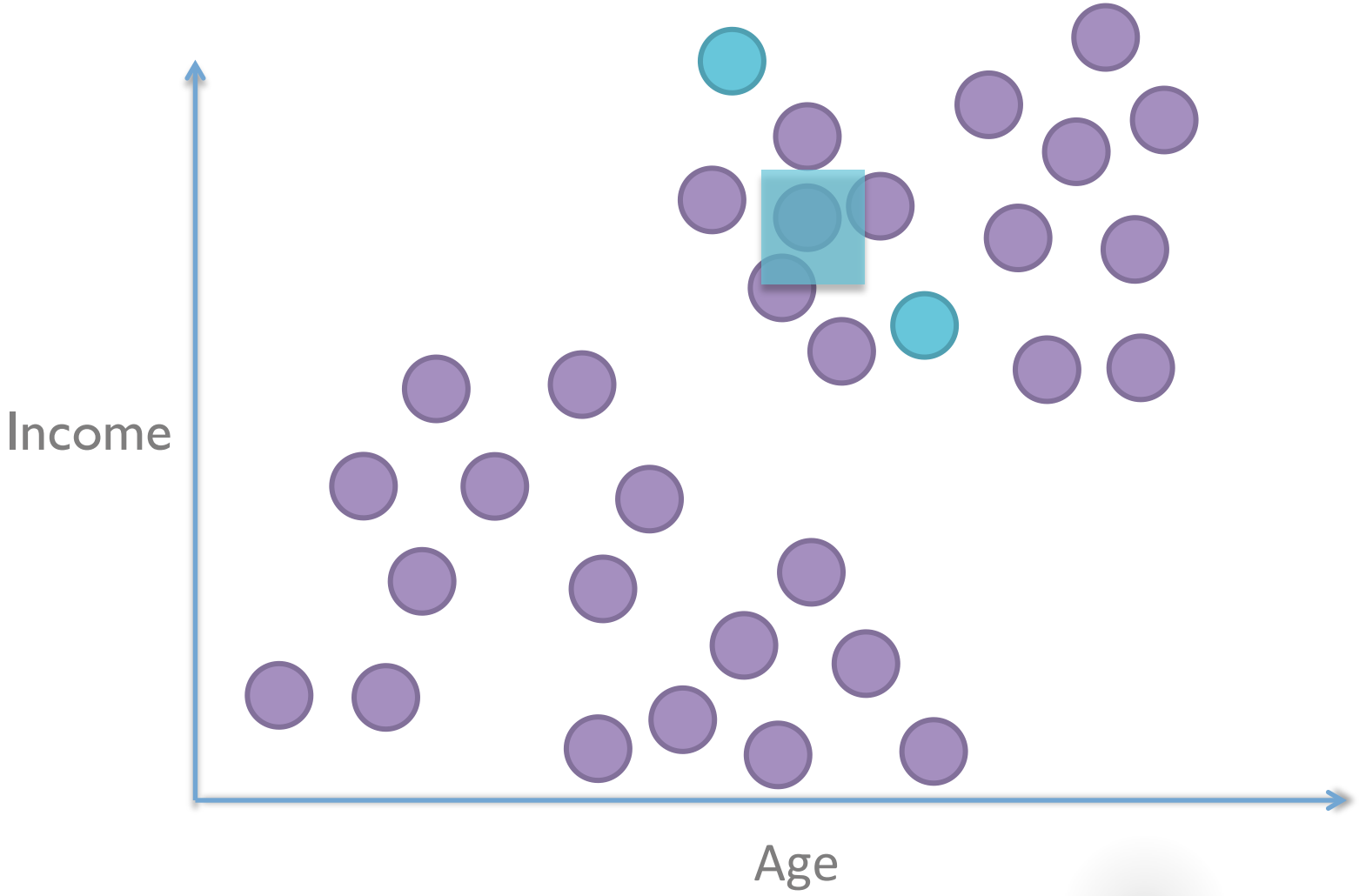
Mean Shift

Sample local density, follow gradient towards denser direction



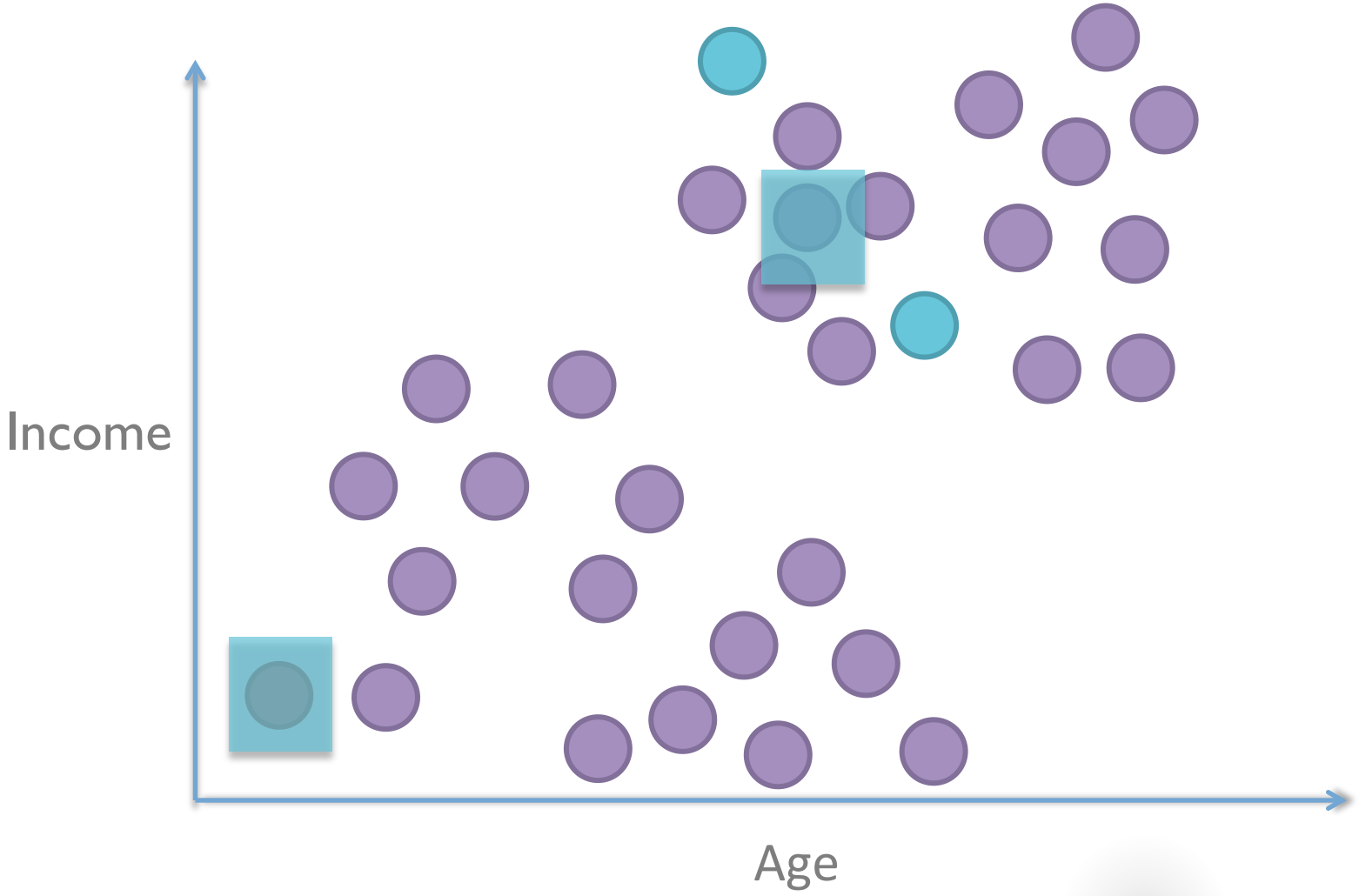
Mean Shift

Found the same (close) local maximum, same cluster



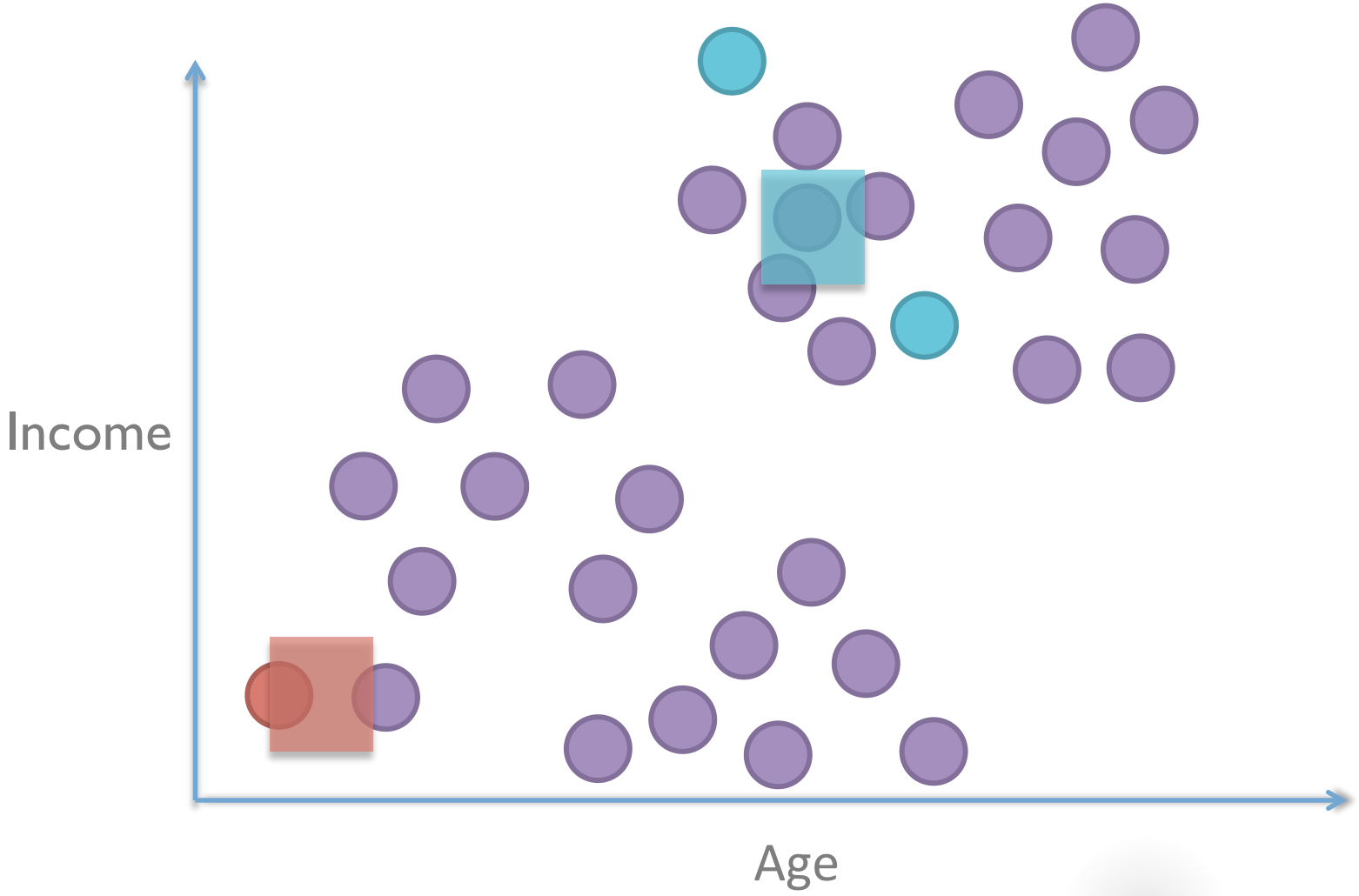
Mean Shift

Start at another point



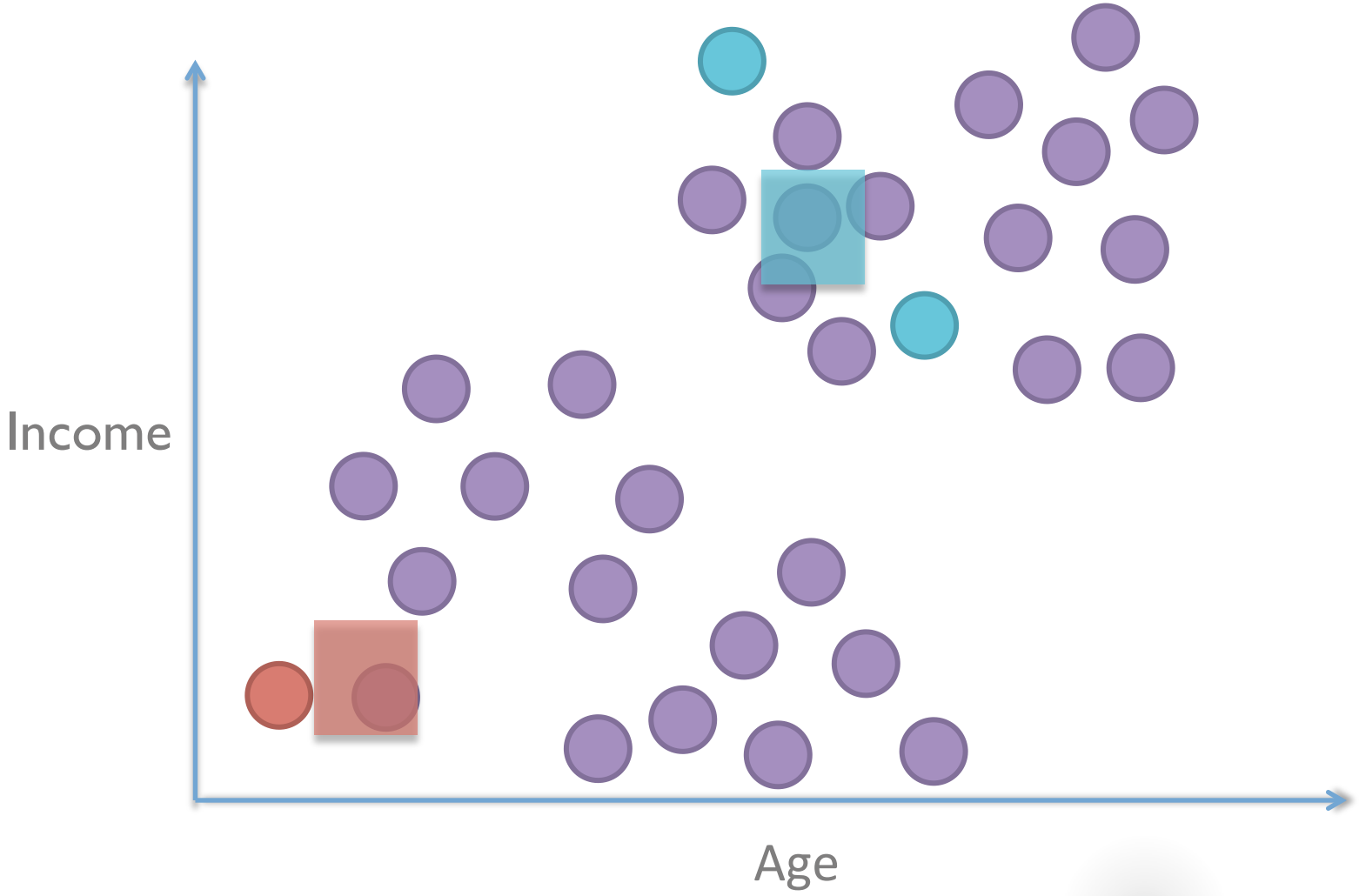
Mean Shift

Sample local density, follow gradient towards denser direction



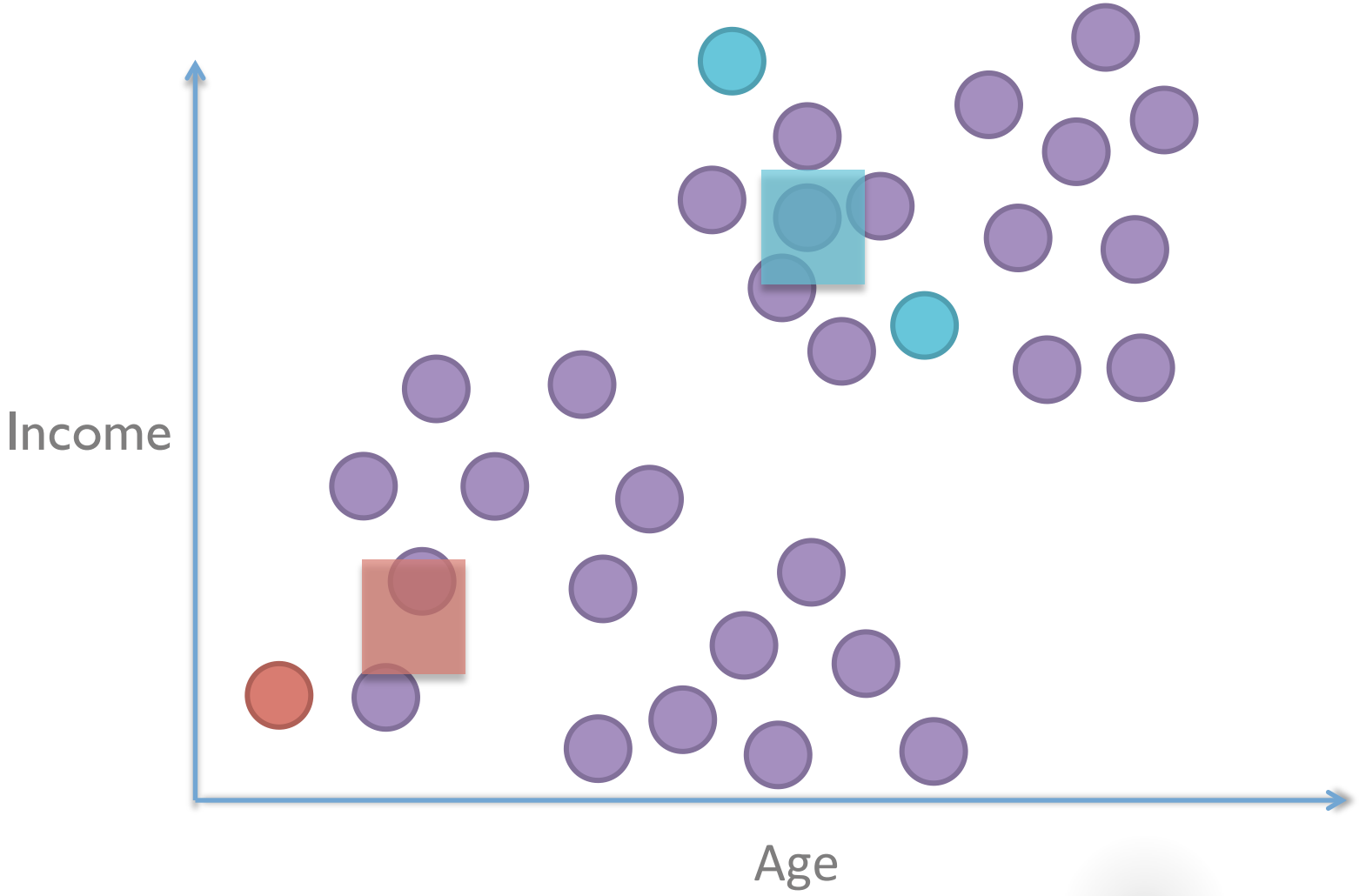
Mean Shift

Sample local density, follow gradient towards denser direction



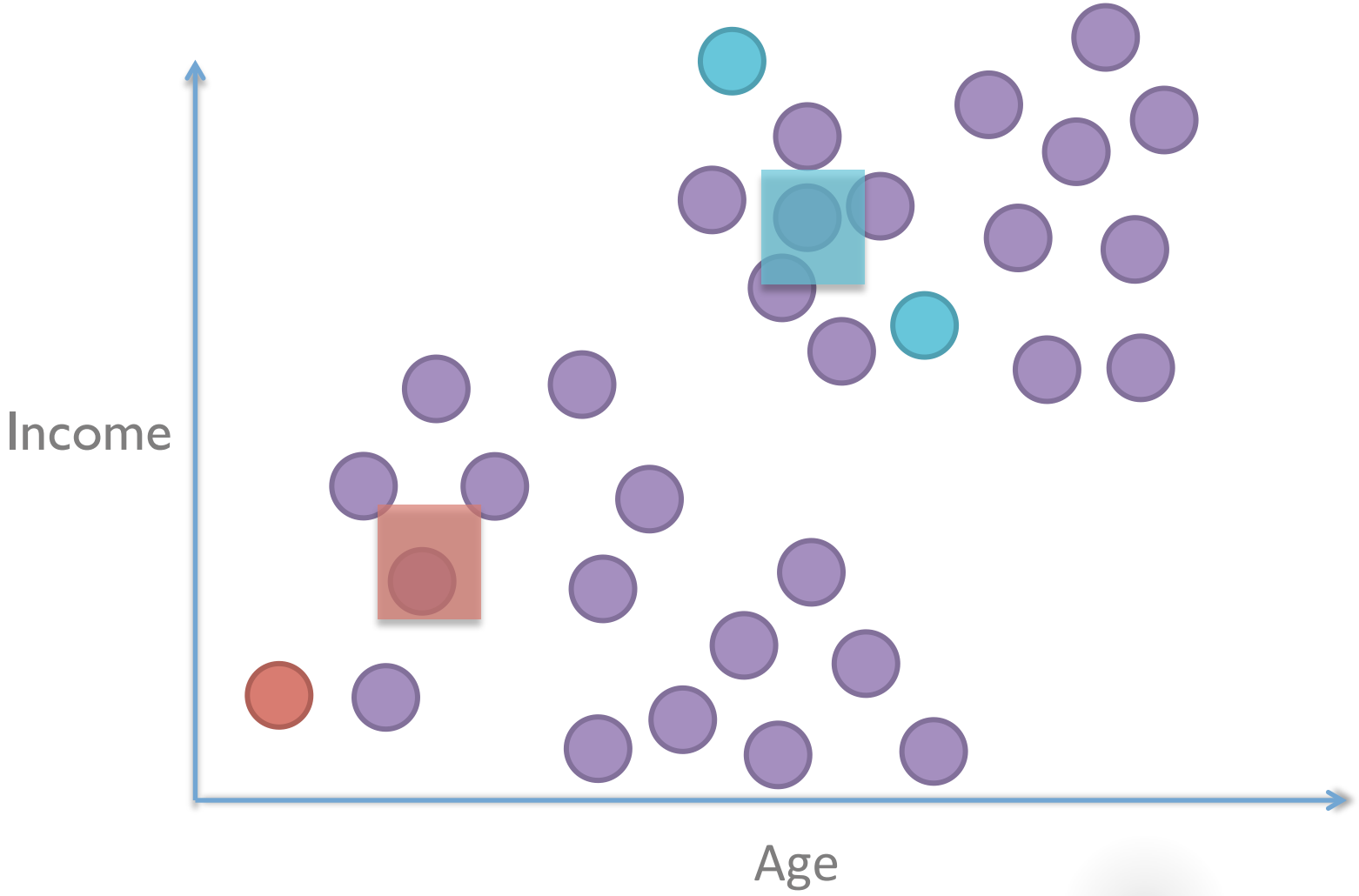
Mean Shift

Sample local density, follow gradient towards denser direction



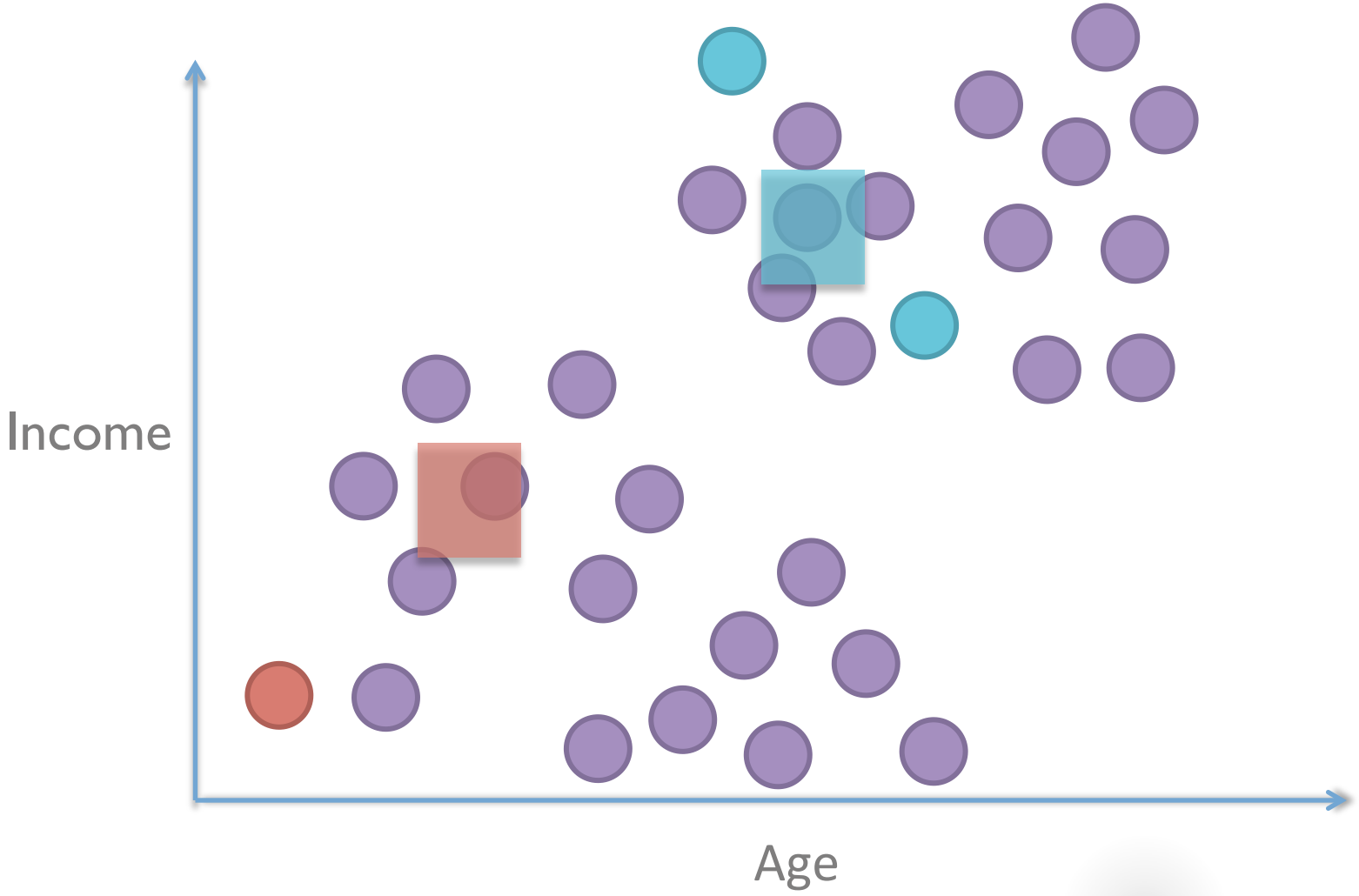
Mean Shift

Sample local density, follow gradient towards denser direction



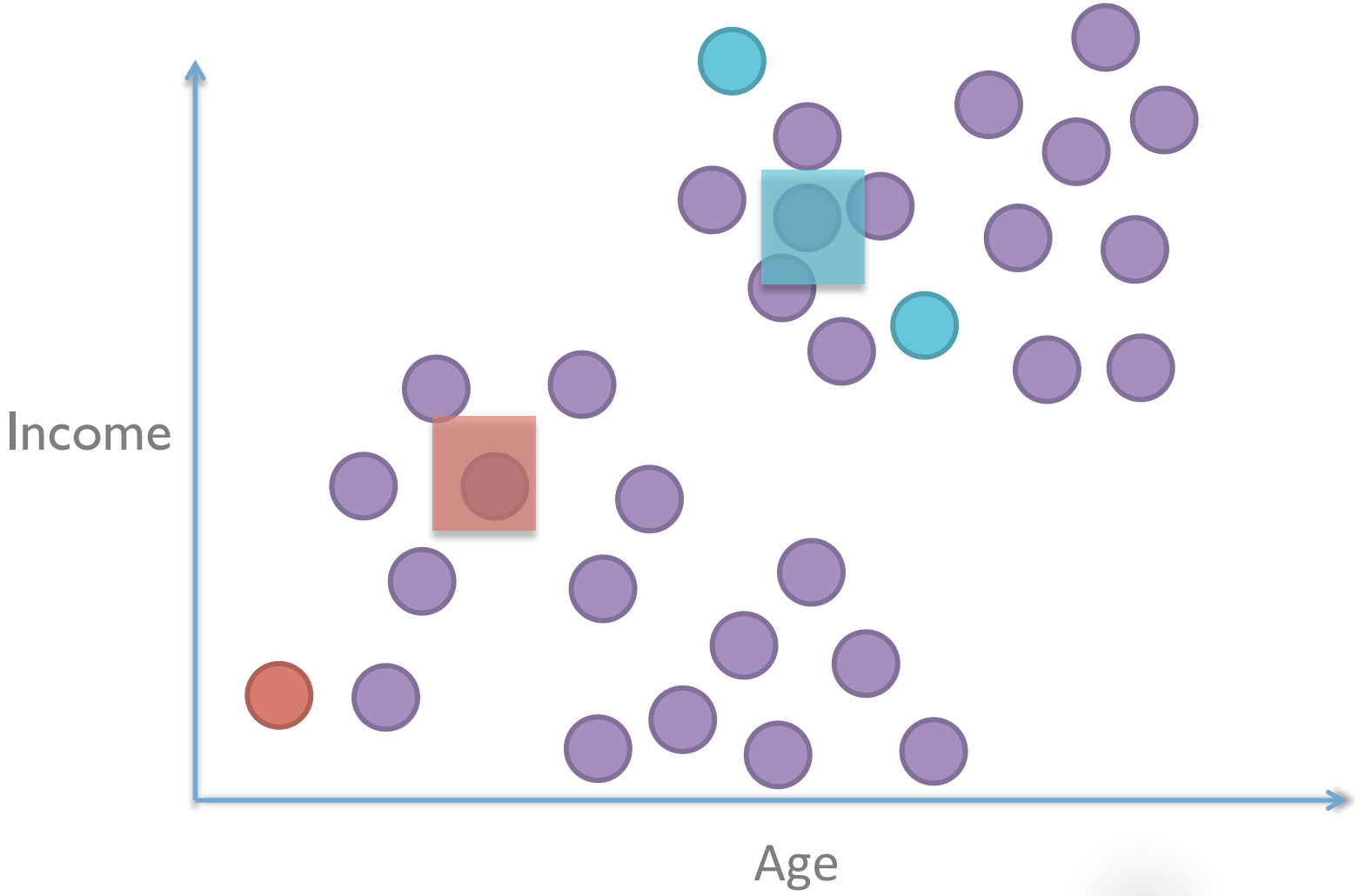
Mean Shift

Sample local density, follow gradient towards denser direction



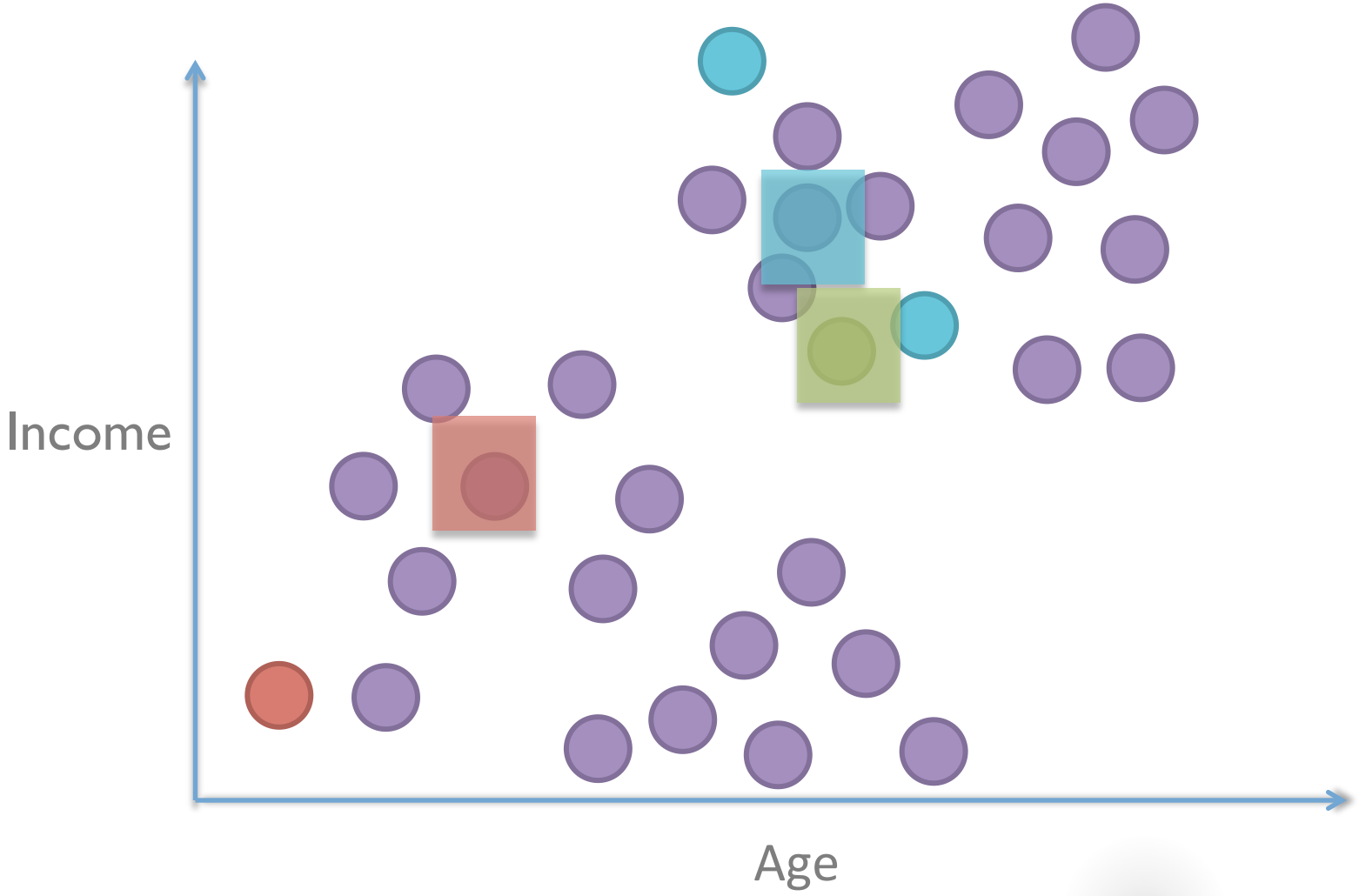
Mean Shift

Found local maximum. Stop.



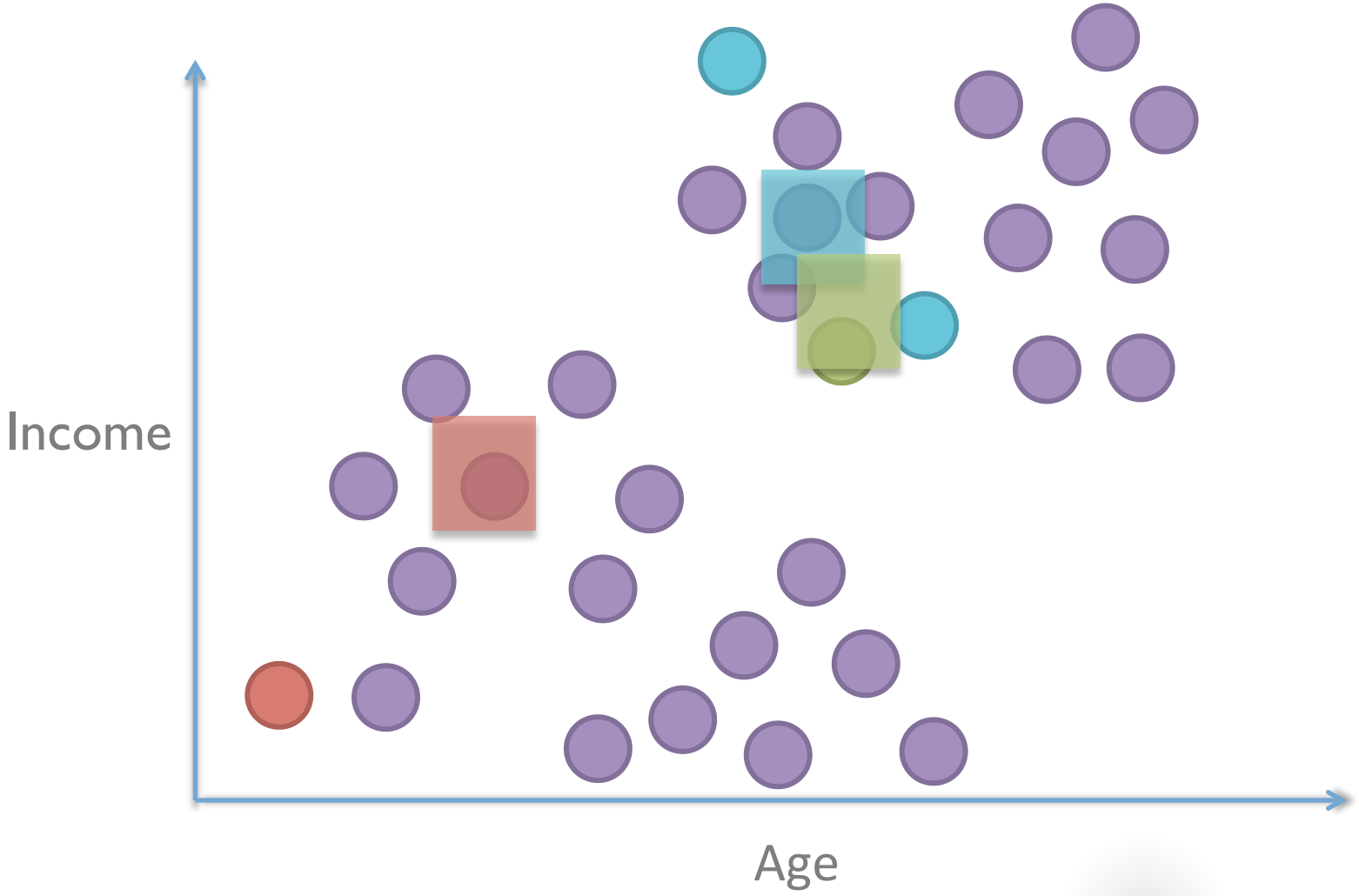
Mean Shift

Start at another point



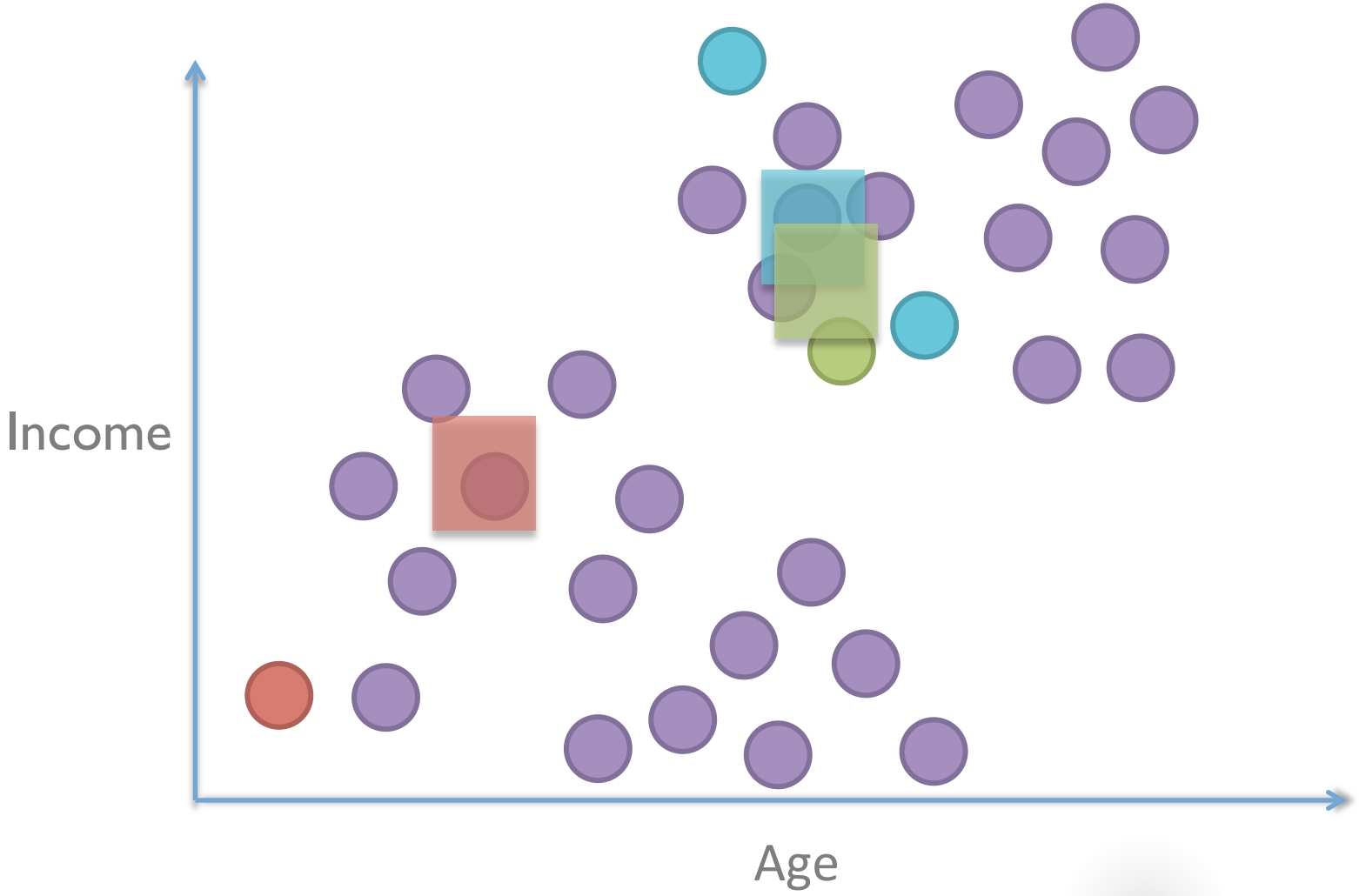
Mean Shift

Search for local density maximum



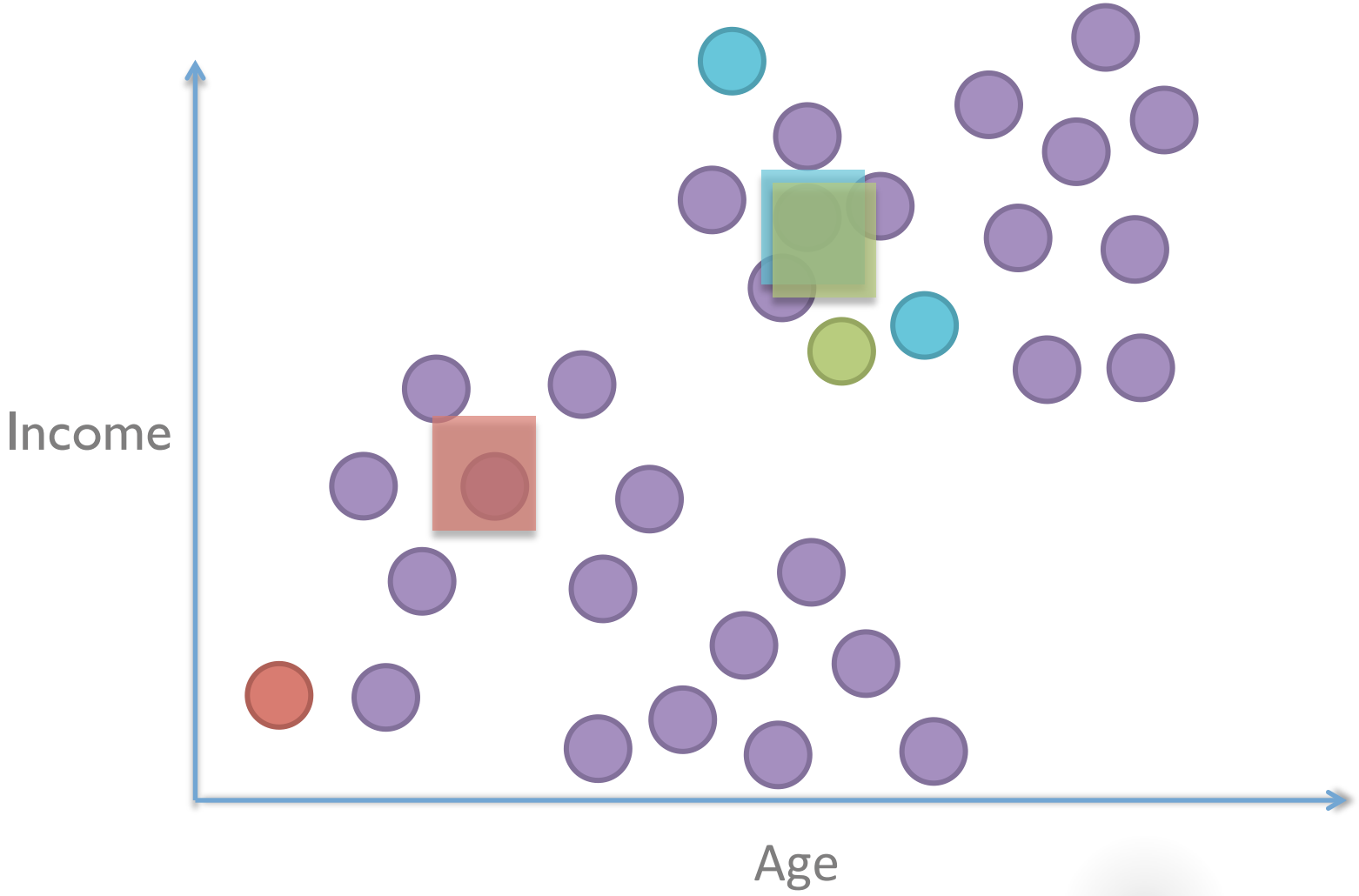
Mean Shift

Search for local density maximum



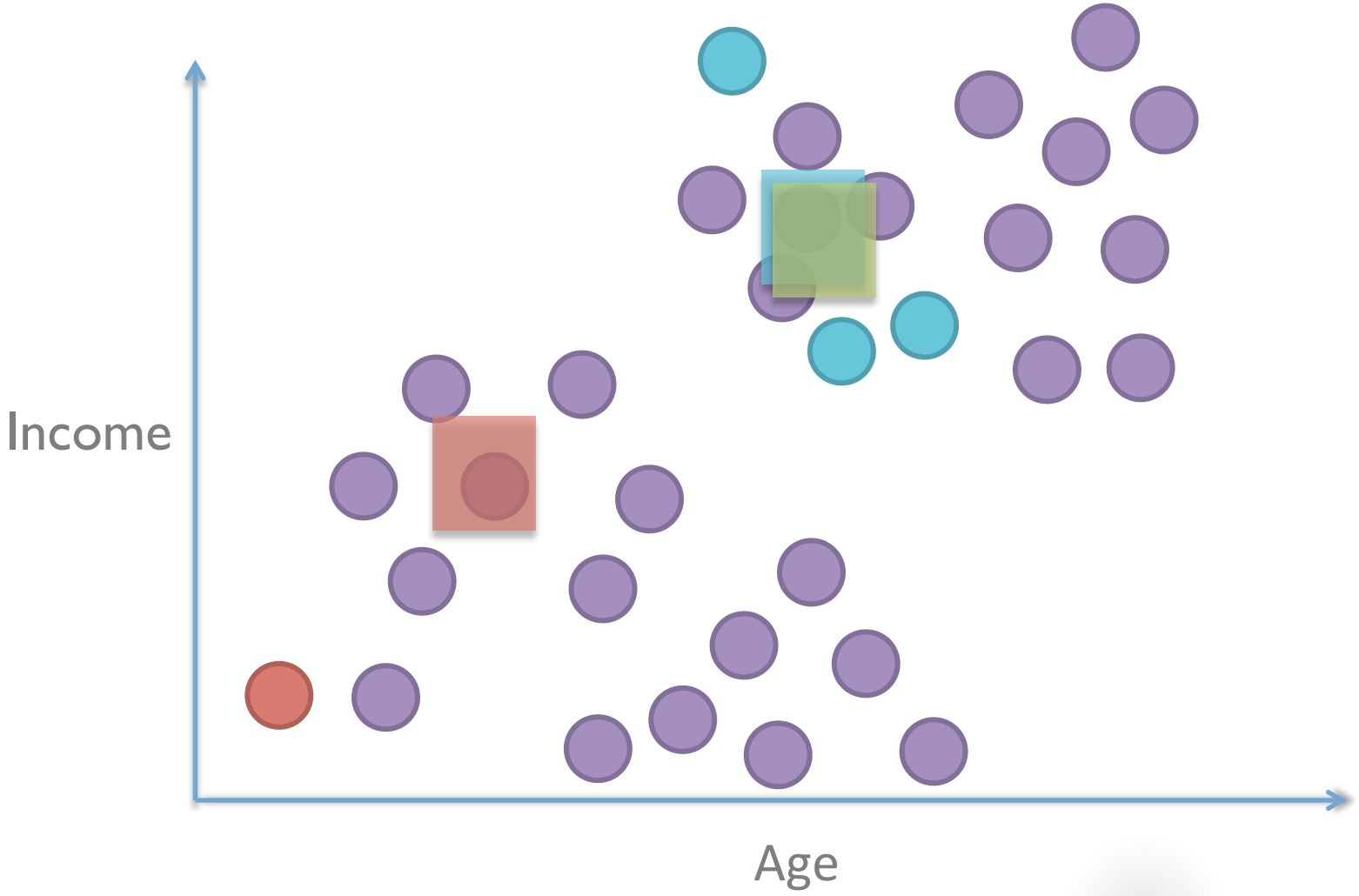
Mean Shift

Found same maximum, same cluster



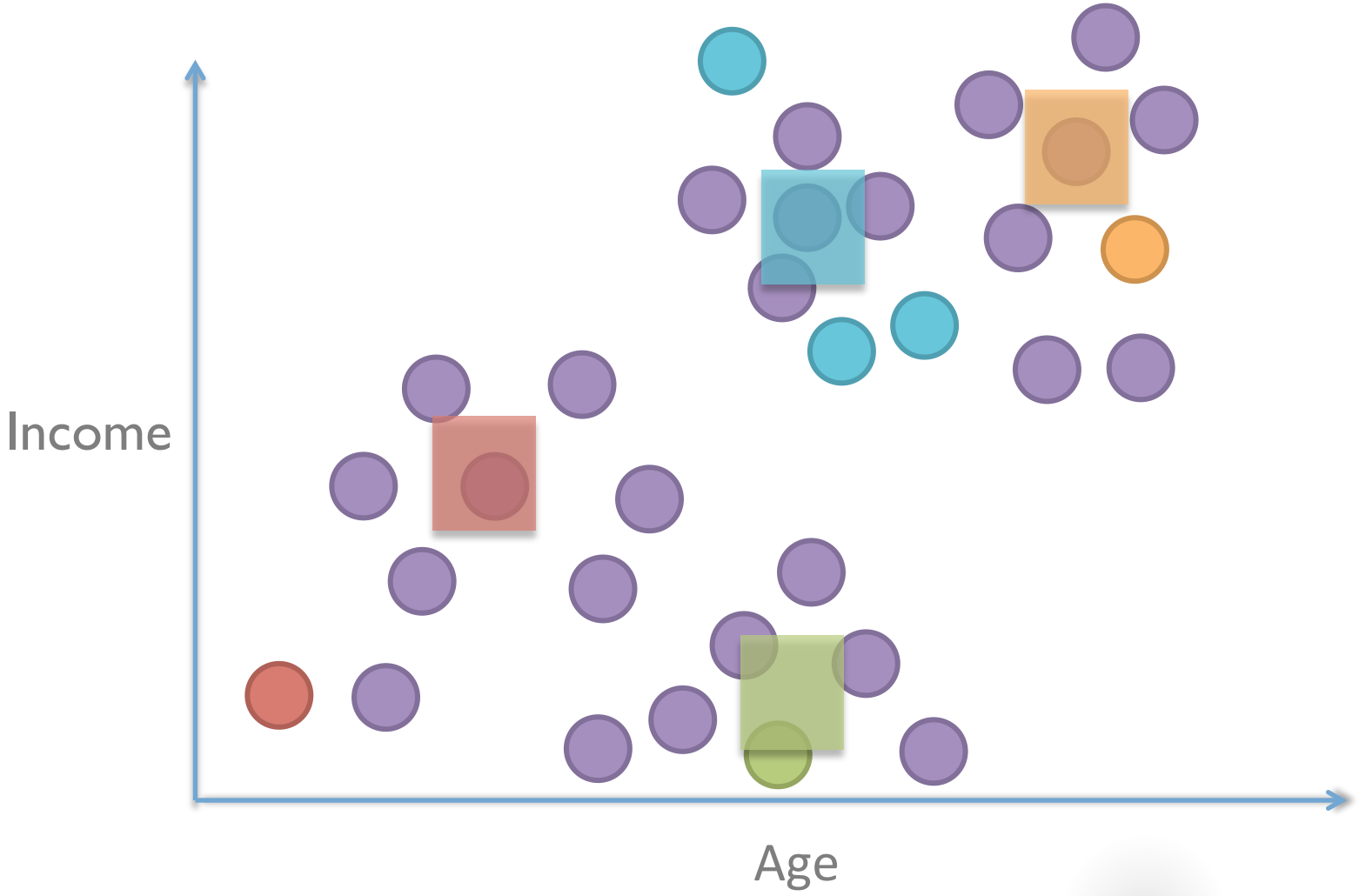
Mean Shift

Found same maximum, same cluster



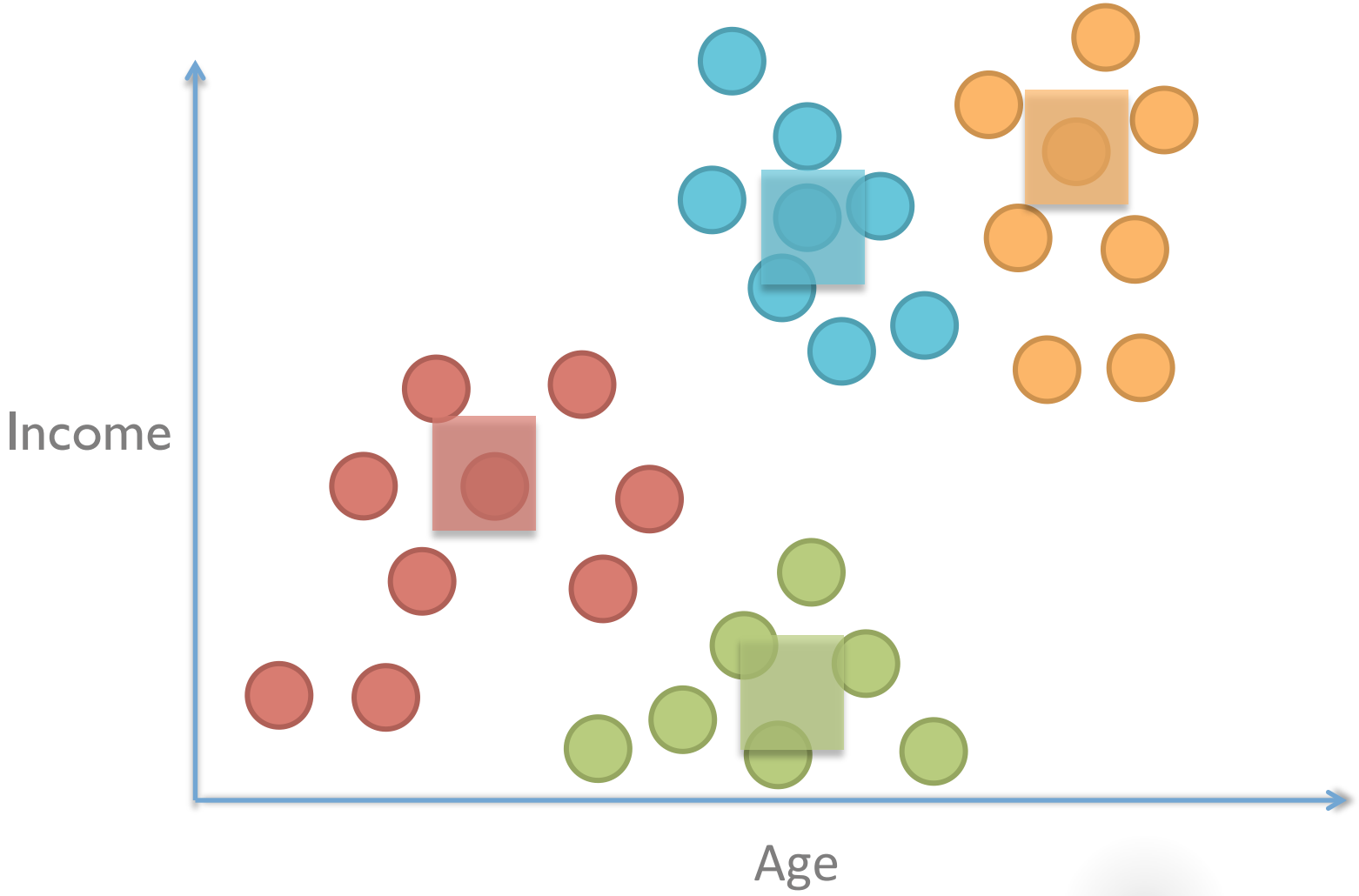
Mean Shift

Keep going like this, eventually it finds four unique local maxima



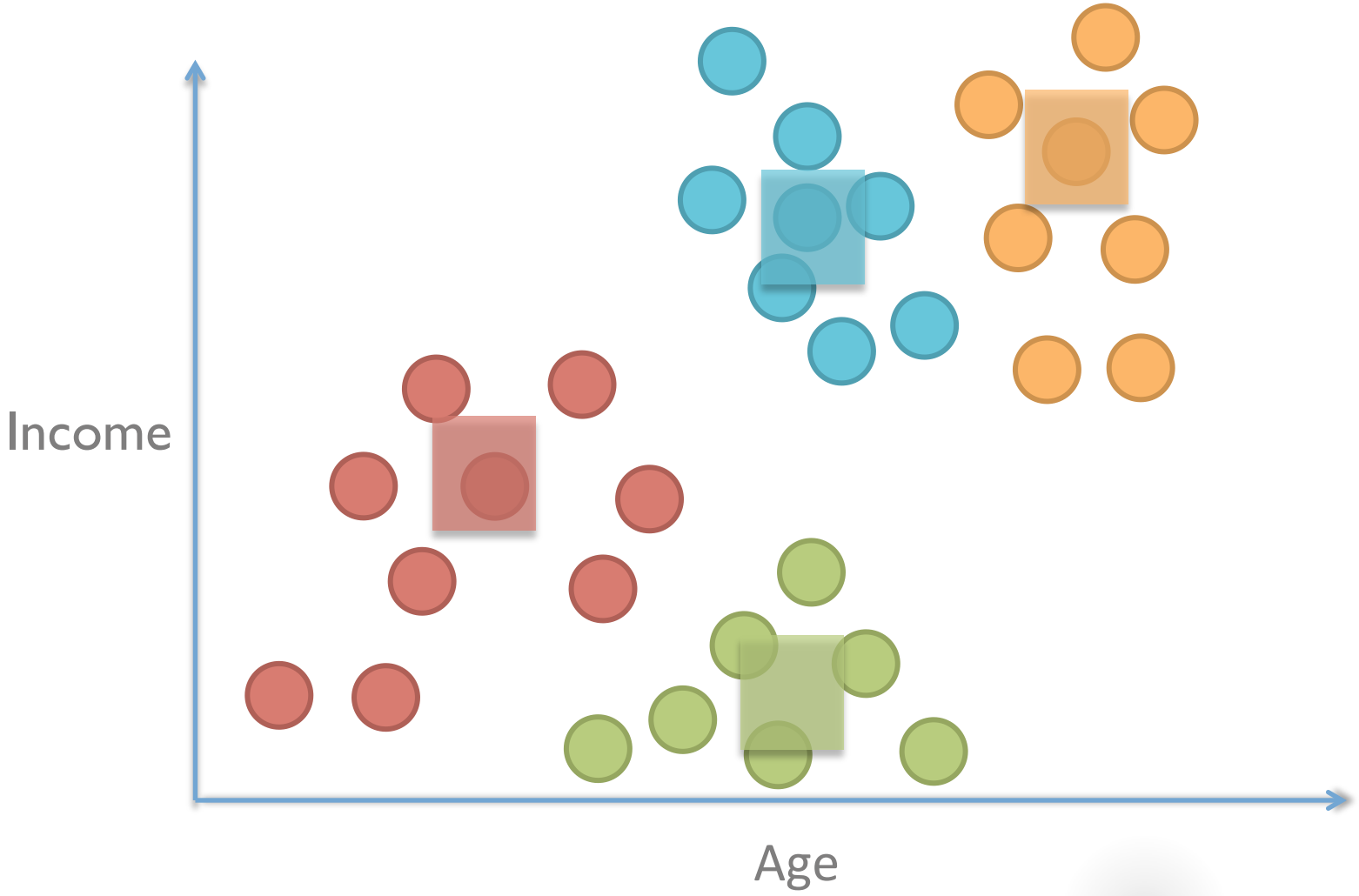
Mean Shift

Assigns points to centroids they fall to



Mean Shift

No cluster number or distance parameters

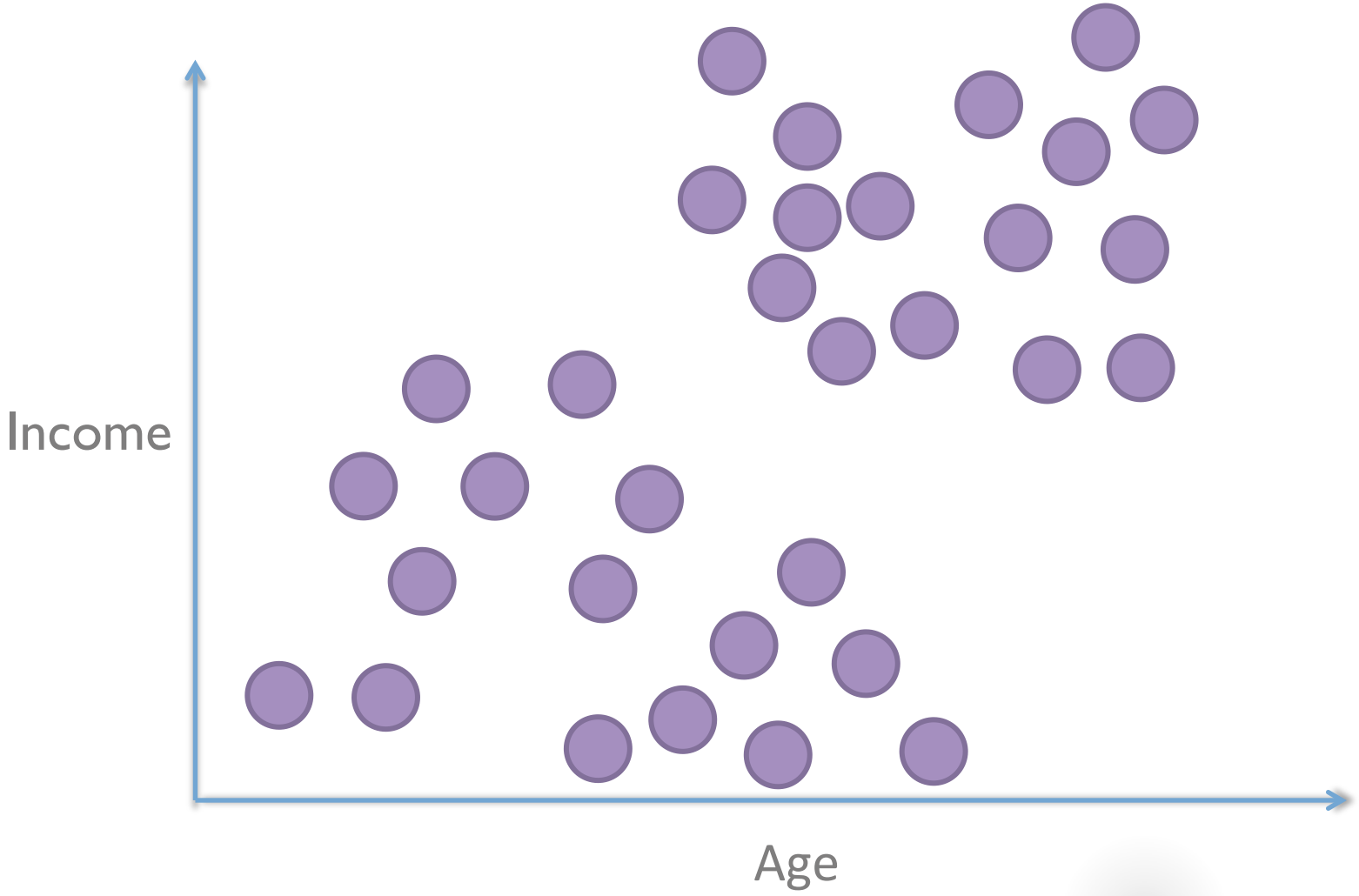


```
from sklearn.cluster import MeanShift

MeanShift()
```

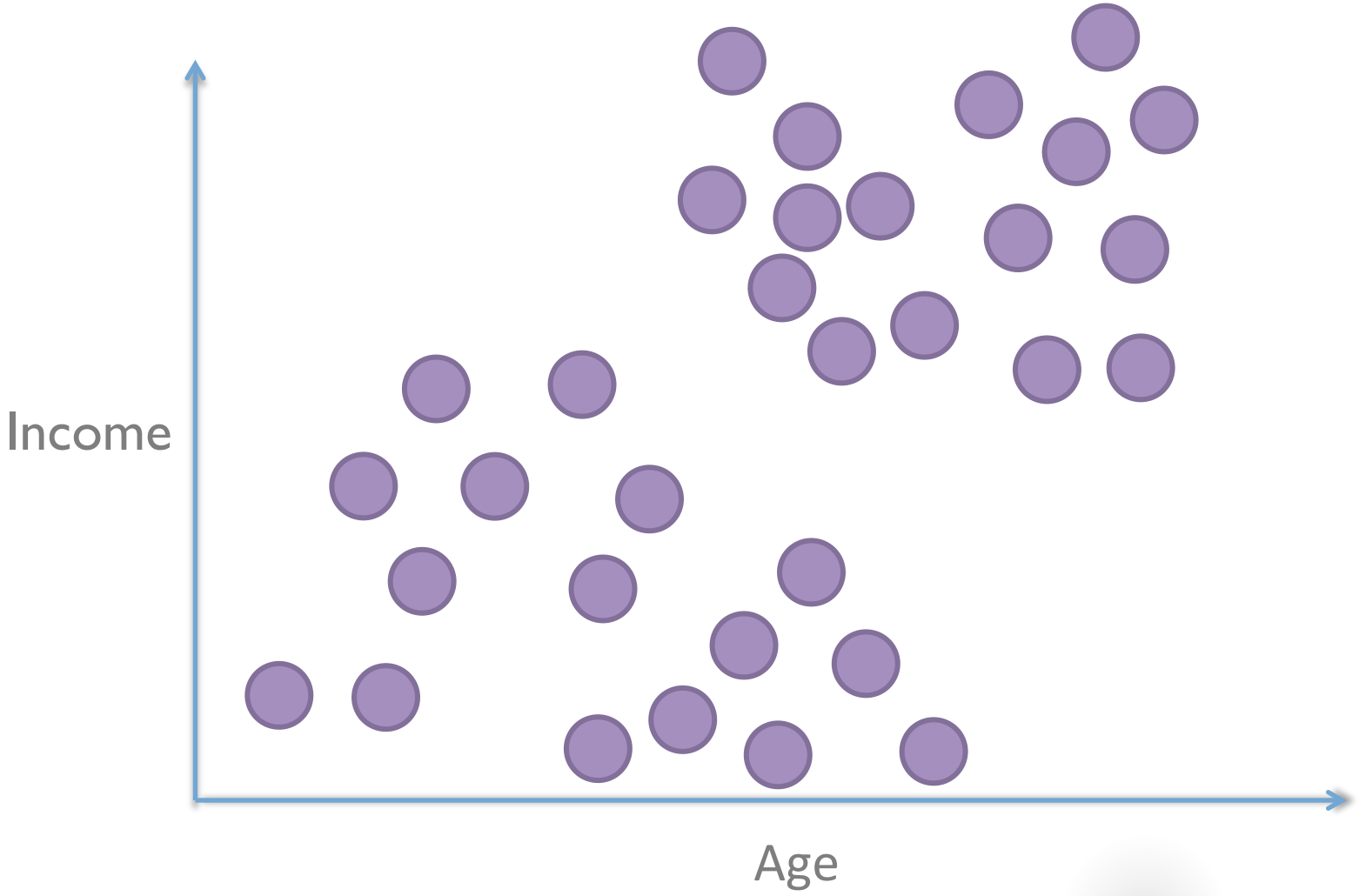
Spectral Clustering
“kernel k-means”

Spectral Clustering



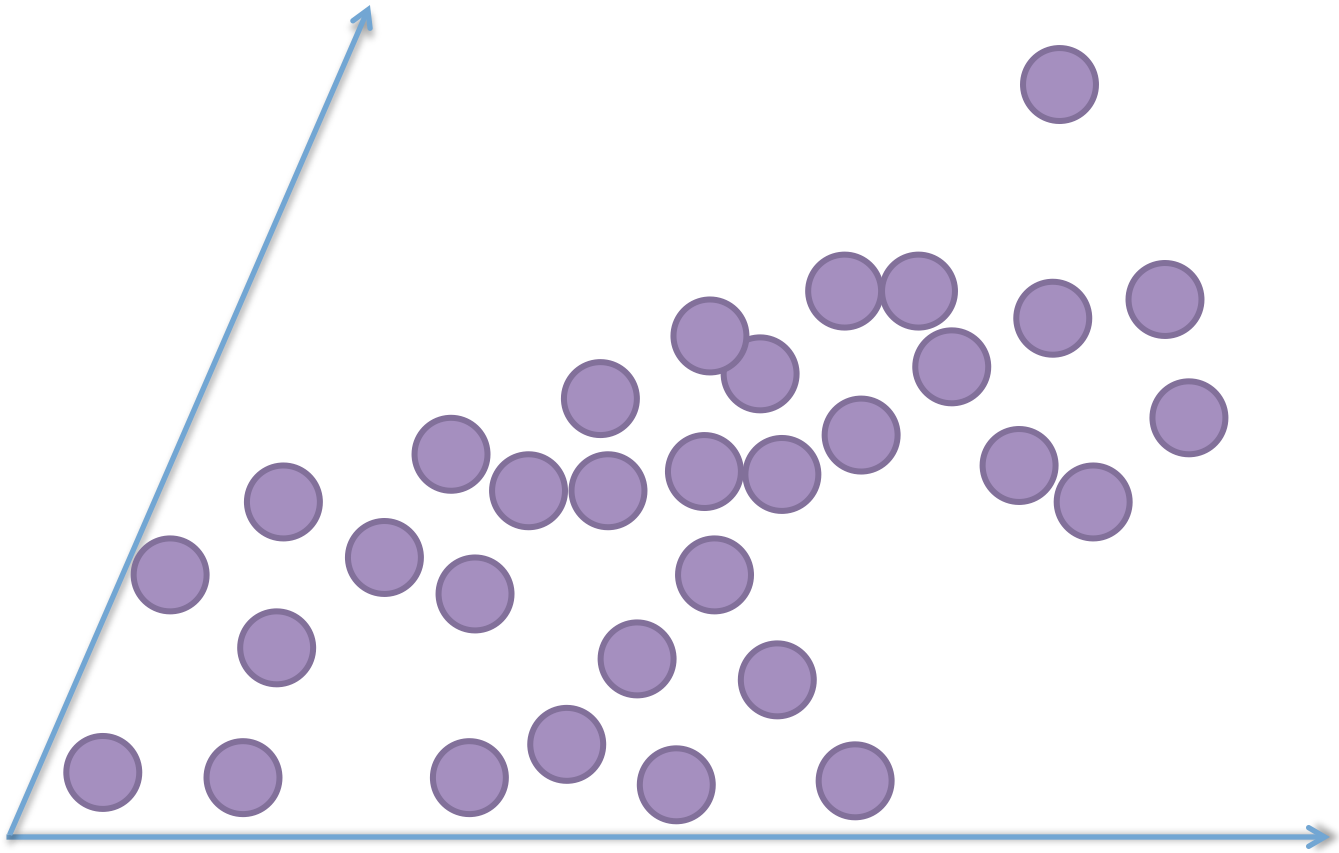
Spectral Clustering

Transform the space into fewer dimensions by taking eigenvectors of the distances matrix



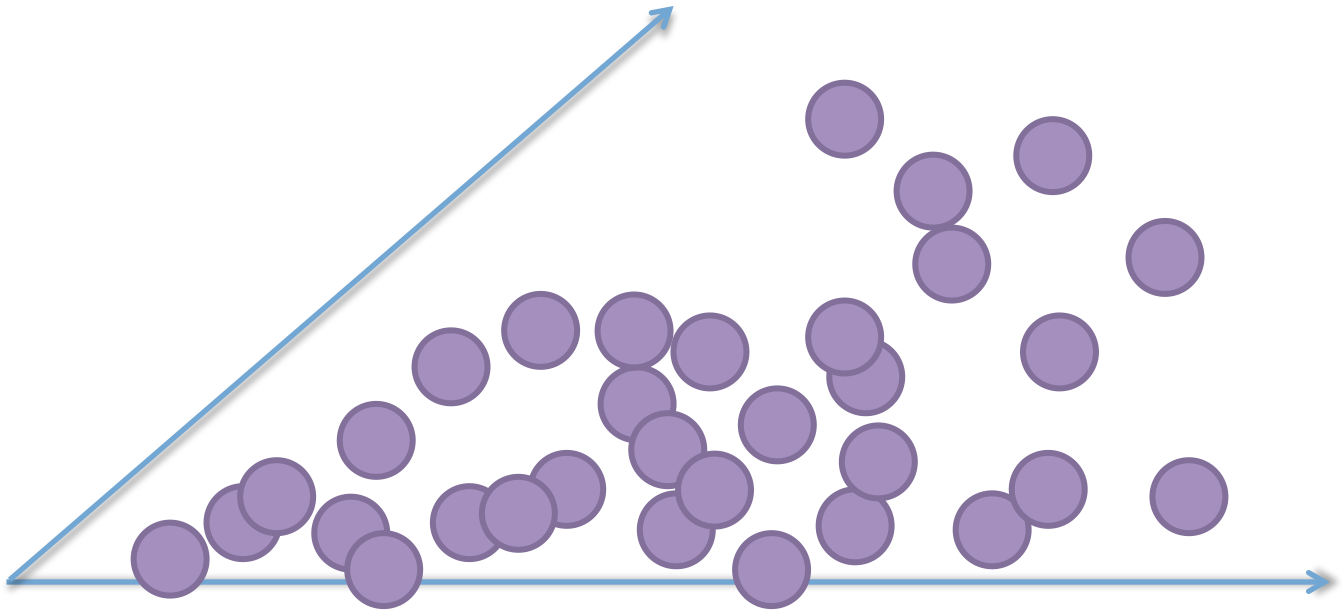
Spectral Clustering

Transform the space into fewer dimensions by taking eigenvectors of the distances matrix



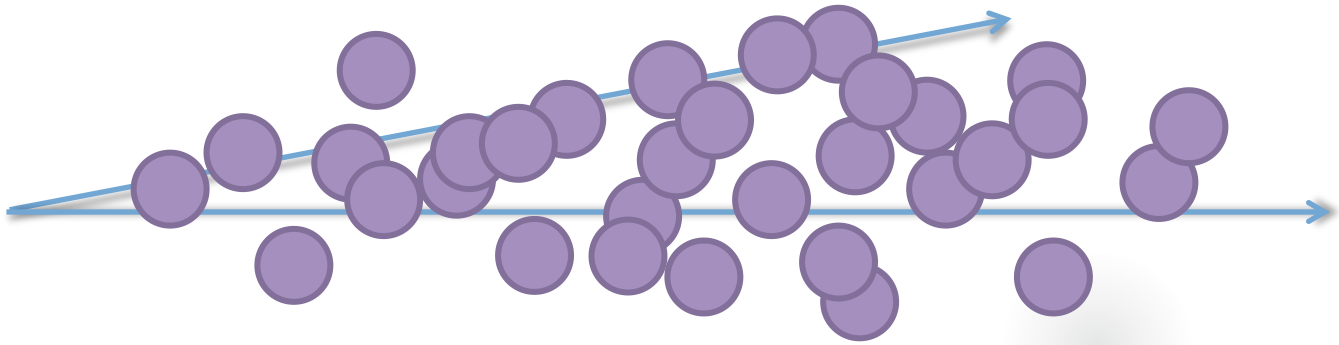
Spectral Clustering

Transform the space into fewer dimensions by taking eigenvectors of the distances matrix



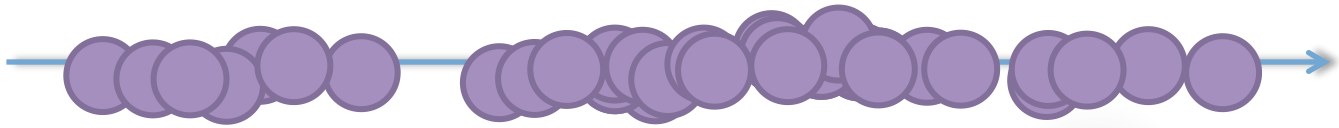
Spectral Clustering

Transform the space into fewer dimensions by taking eigenvectors of the distances matrix



Spectral Clustering

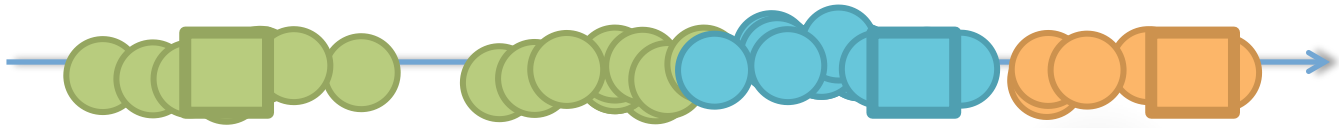
Transform the space into fewer dimensions by taking eigenvectors of the distances matrix



0.7 Income + 0.3 Age

Spectral Clustering

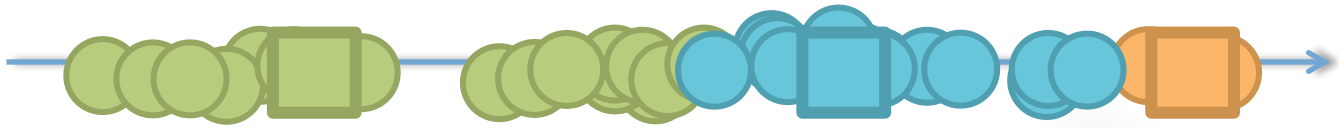
Now perform K-Means on the low dimension space (k=3)



0.7 Income + 0.3 Age

Spectral Clustering

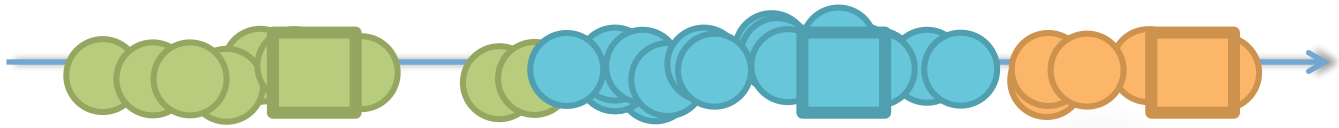
Now perform K-Means on the low dimension space



0.7 Income + 0.3 Age

Spectral Clustering

Now perform K-Means on the low dimension space



0.7 Income + 0.3 Age

Spectral Clustering

Now perform K-Means on the low dimension space

0.7 Income + 0.3 Age

Spectral Clustering

Now perform K-Means on the low dimension space

0.7 Income + 0.3 Age

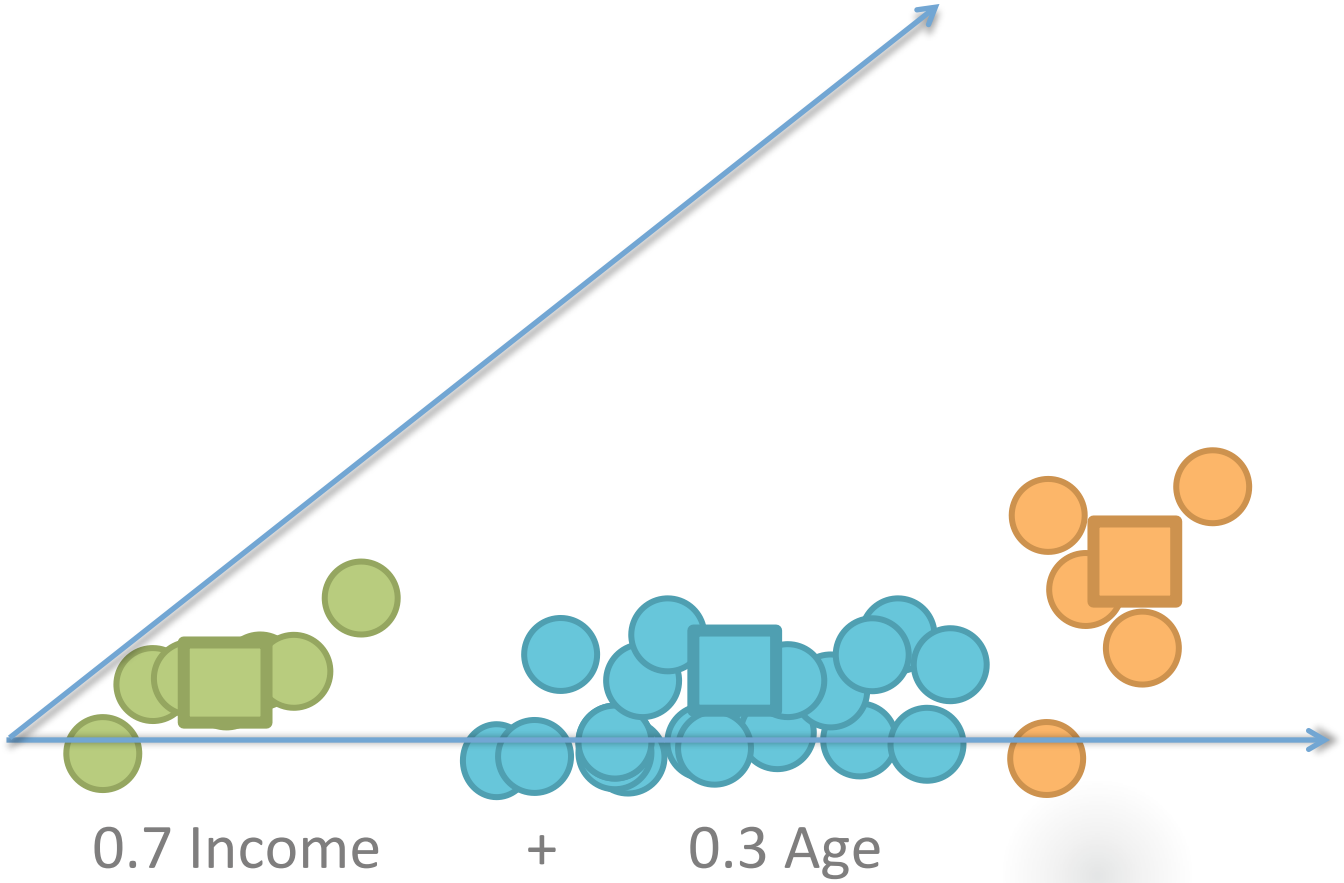
Spectral Clustering

Look at them in the normal space

0.7 Income + 0.3 Age

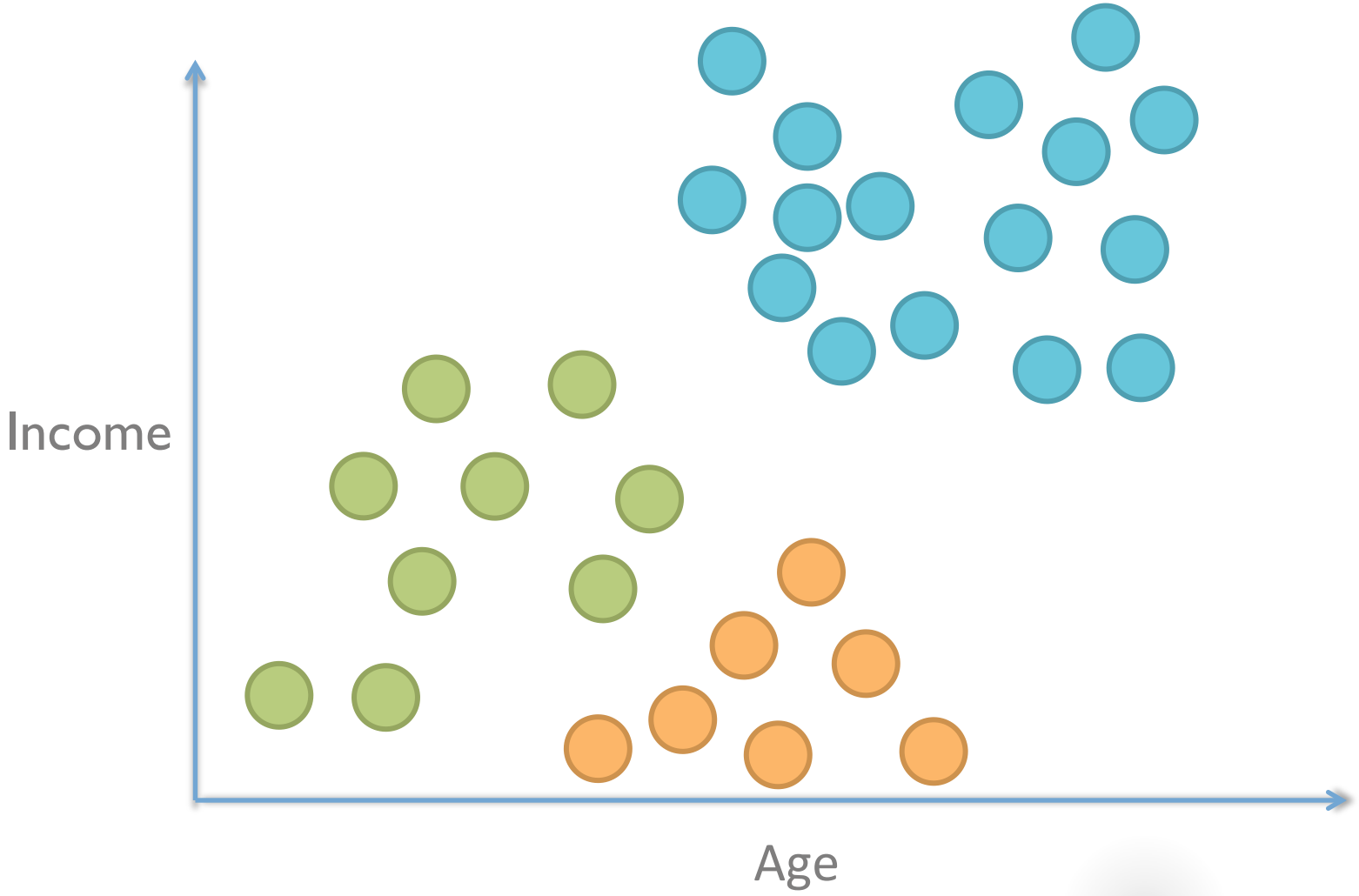
Spectral Clustering

Look at them in the normal space



Spectral Clustering

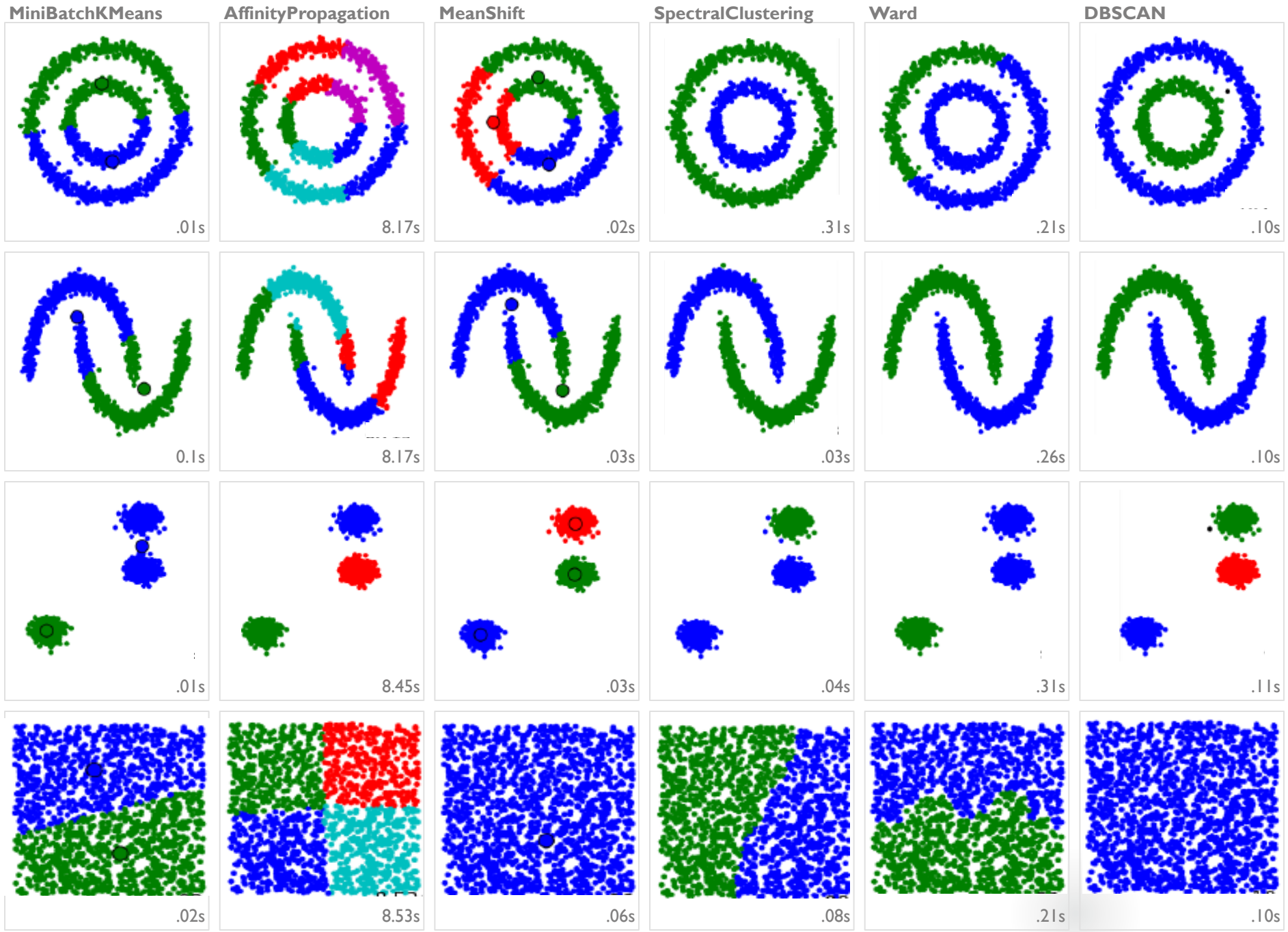
Look at them in the normal space



```
from sklearn.cluster import
SpectralClustering

SpectralClustering( n_clusters=8, n_init=10 )
```

Properties, Advantages, Disadvantages


MiniBatchKMeans
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Method name	Parameters	Scalability	Usecase	Geometry (metric used)
K-means	Number of clusters	Very large *n_samples* medium *n_clusters* with *MiniBatch code*	General purpose, even cluster size, flat geometry, not too many clusters	Distances between points
Affinity propagation	Damping, sample preferences	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry	Graph distance (e.g. nearest-neighbor graph)
Mean-shift	Bandwidth	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry	Distances between points
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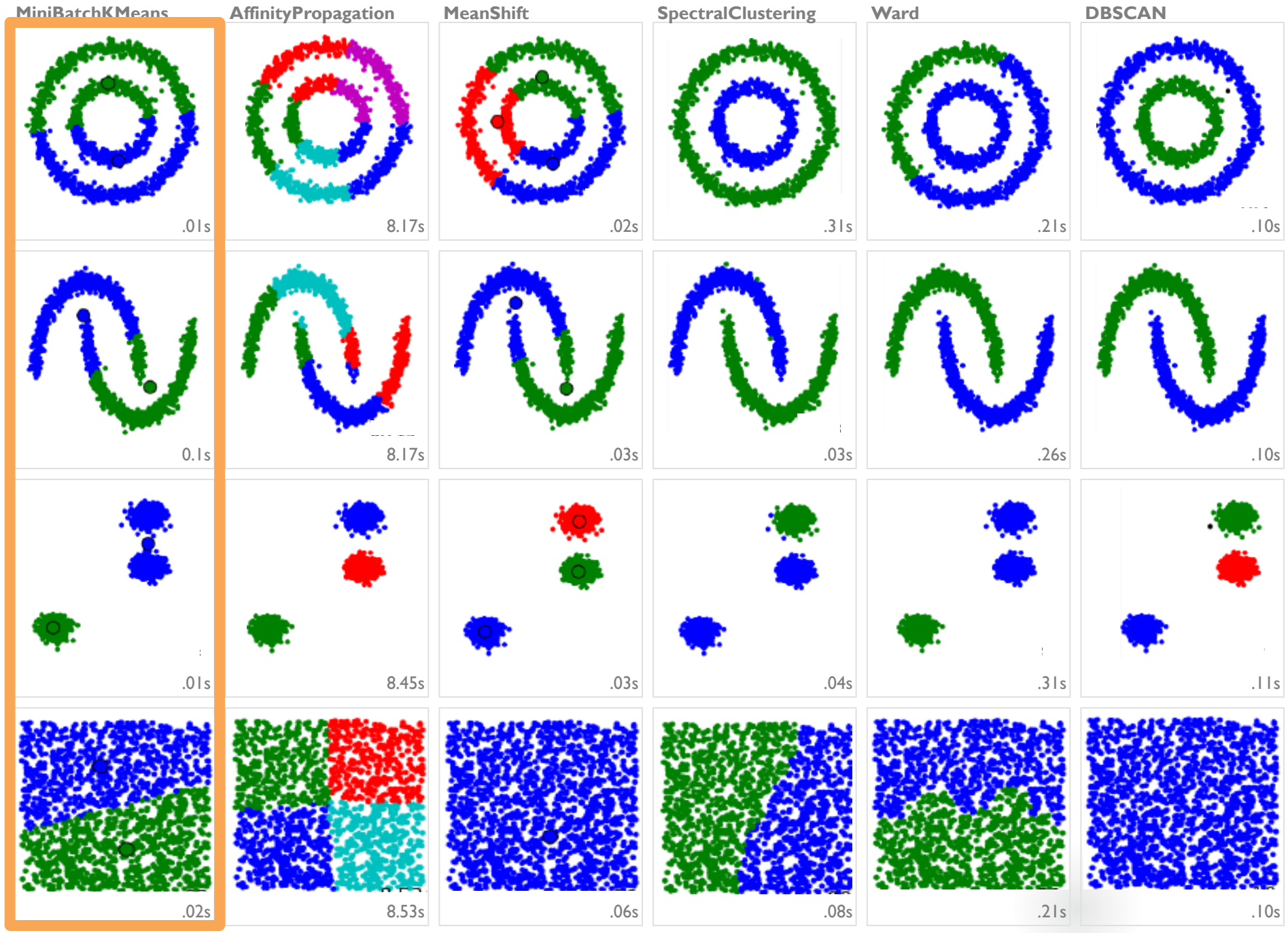
K Means:

- MiniBatch version is super fast (big data).
- Have to try k values (k not too big).
- Tends to find even sized.
- Bad with non-spherical cluster shapes.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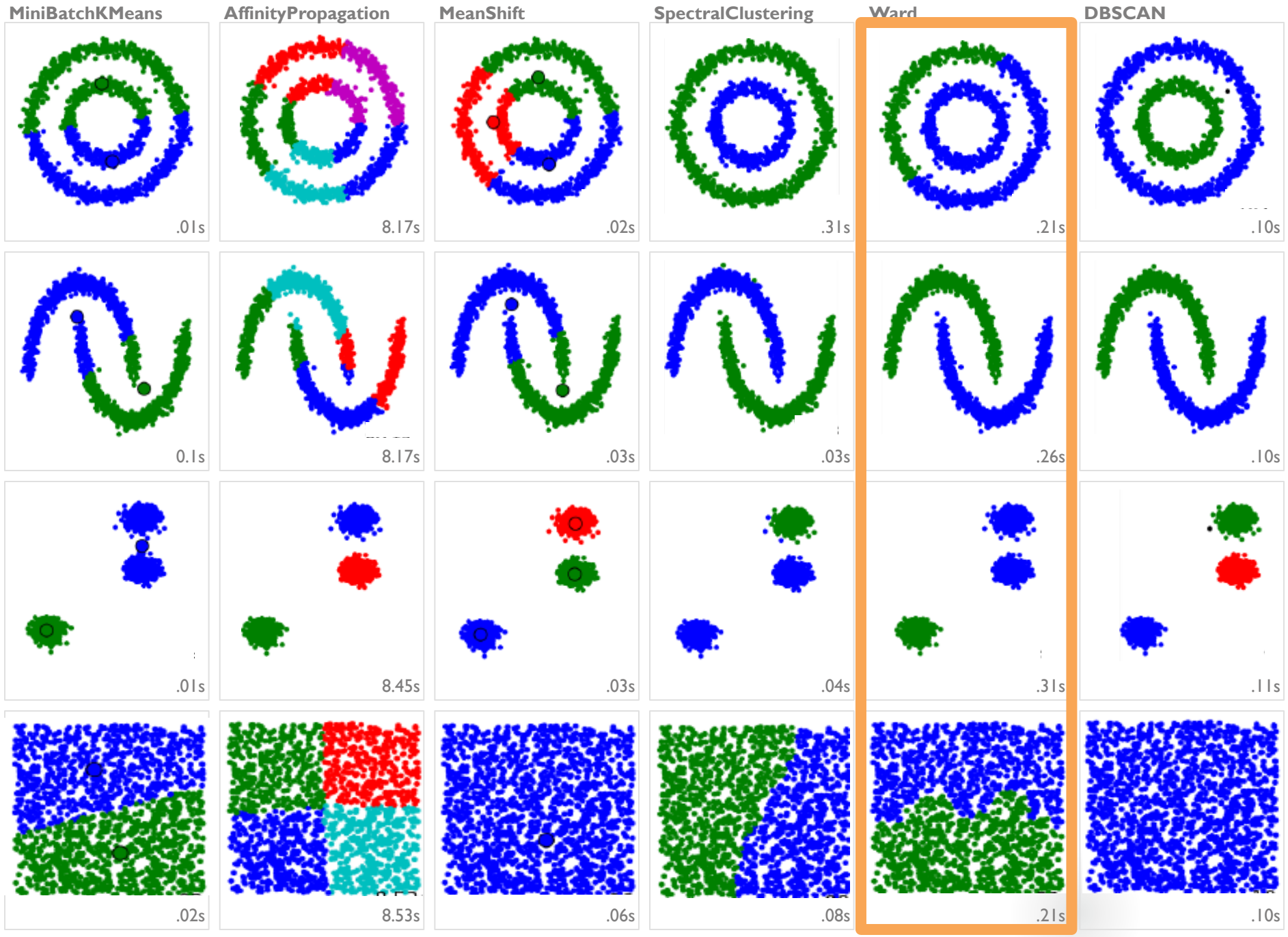
Hierarchical Clustering:

- You get a full hierarchy tree. Useful for some problems.
- Have to try k values.
- Finds uneven cluster sizes (one is big, some are tiny, etc.). Due to the "the chains get chainier effect."
- A lot of distance metric and linkage options.
- Slow: O(n^2).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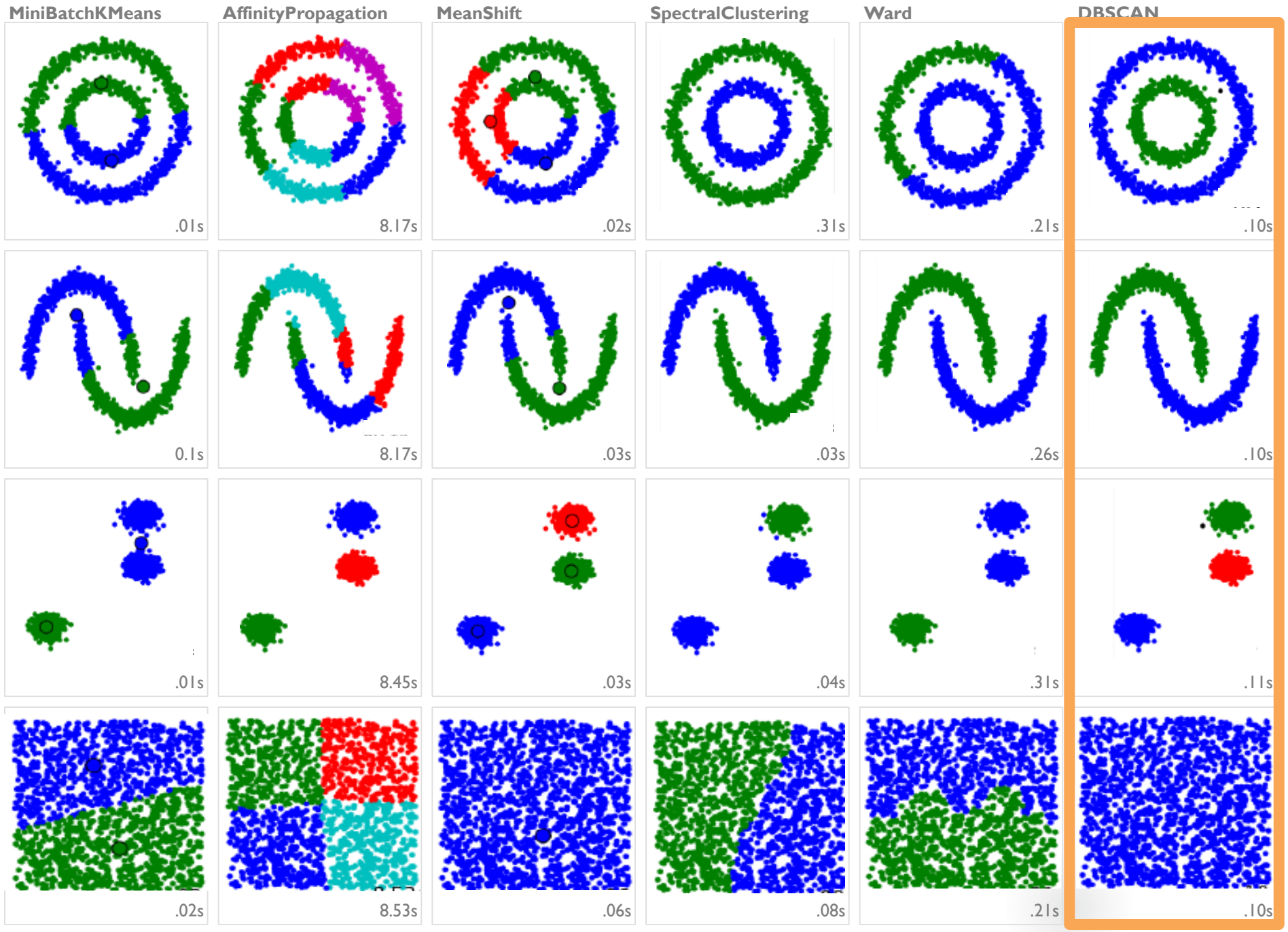
DBSCAN

Density based, on the money with the right parameters.
Have to try *epsilon* (and *num_clu*) values.
Can find uneven cluster sizes.
Full distance metric options.
Can handle tons of data and weird shapes.
Too small epsilon (too many clusters) is a bit shaky.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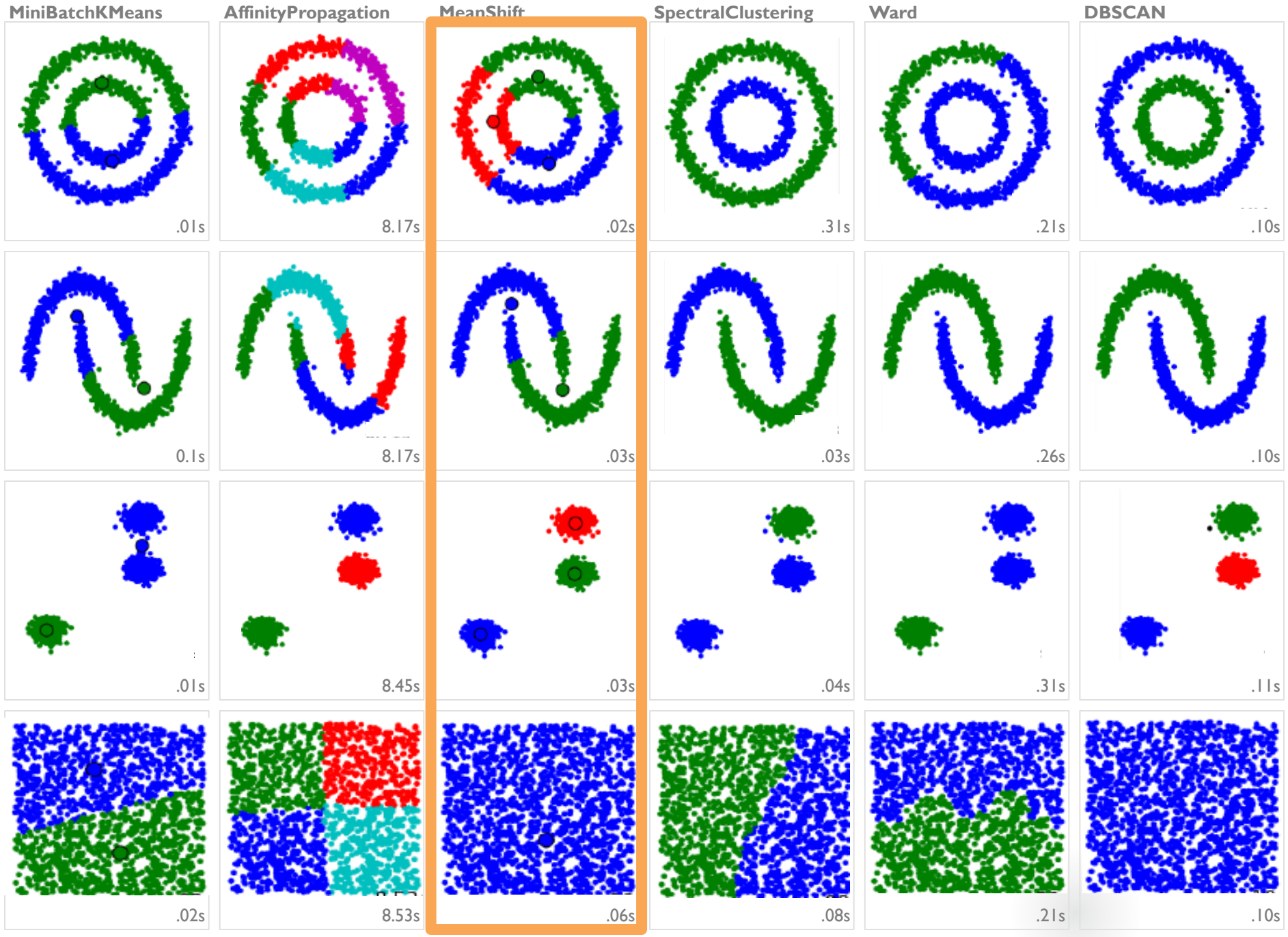
Mean-shift

- You DON'T have to guess k or other parameters. Fire & forget.
- Can find uneven cluster sizes.
- Slow with a lot of data, but lots of clusters no problem
- Doesn't handle weird shapes well.

Euclidean distance only.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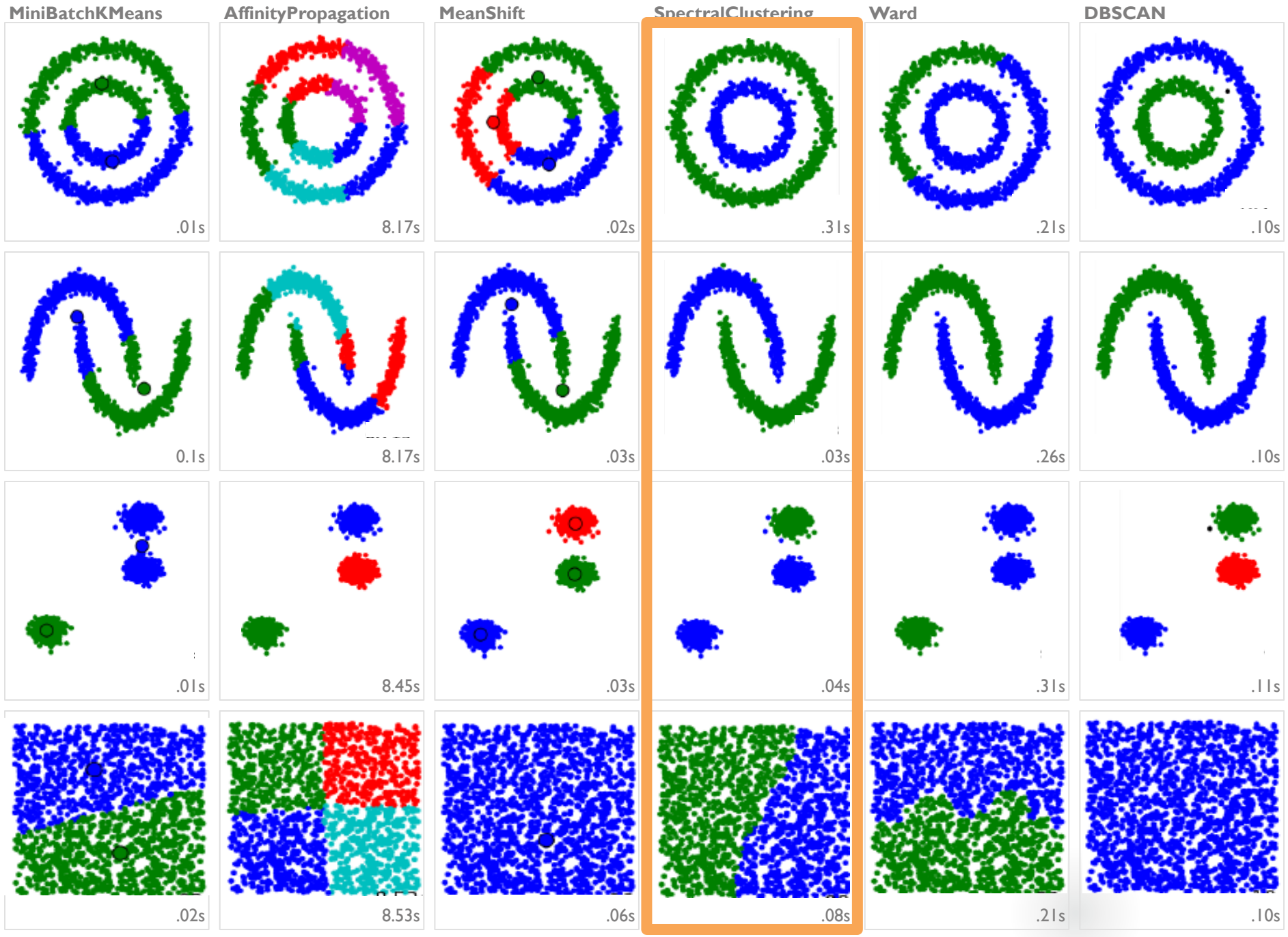
Spectral clustering:

- Best with sparse distances.
- Tends to find even sized clusters.
- Good with only a few clusters, rubbish with many.
- Can handle weirdest connectivity shapes (like concentric circles)
- Euclidean distance only.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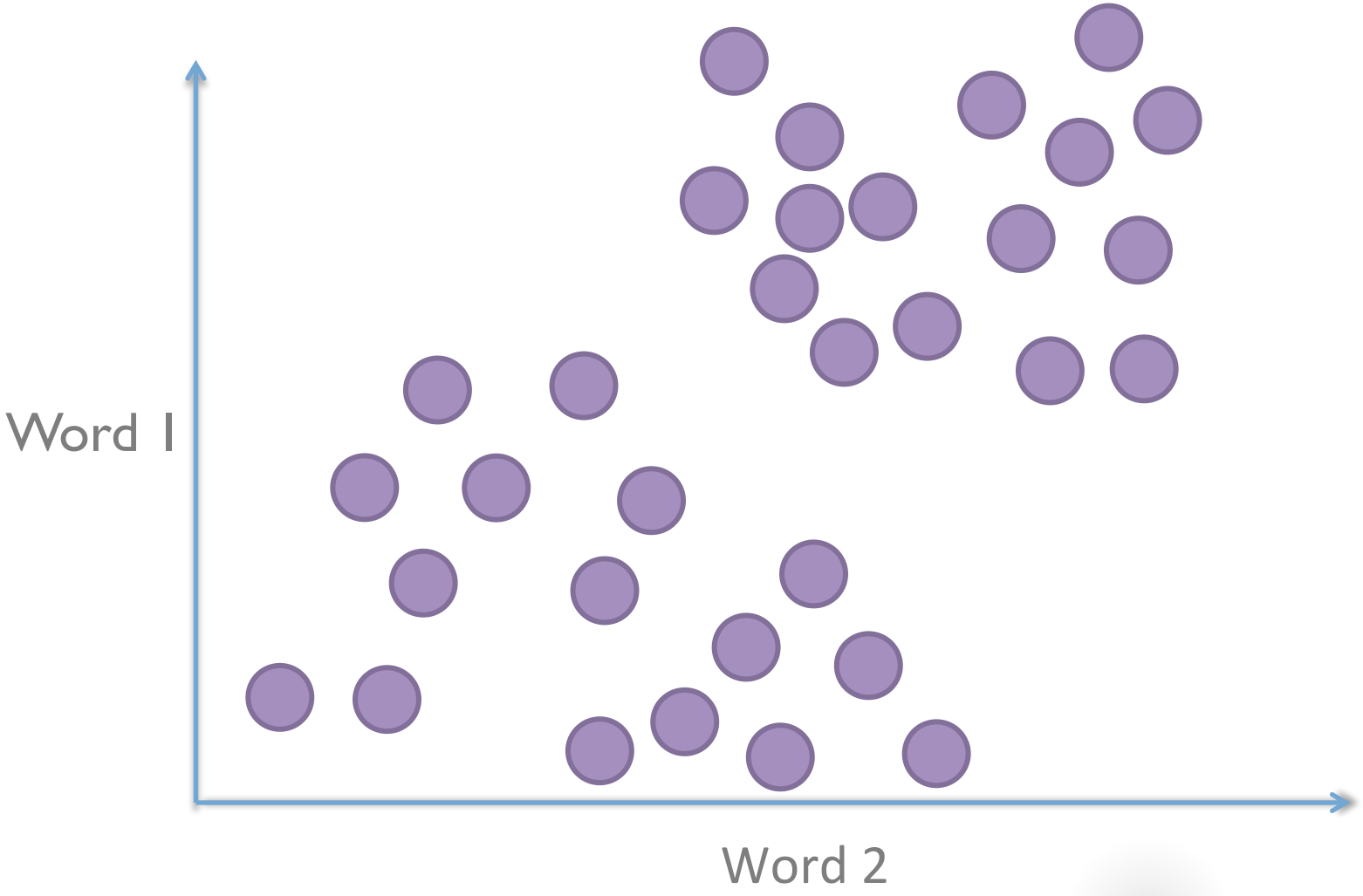
What does clustering with cosine distance look like?

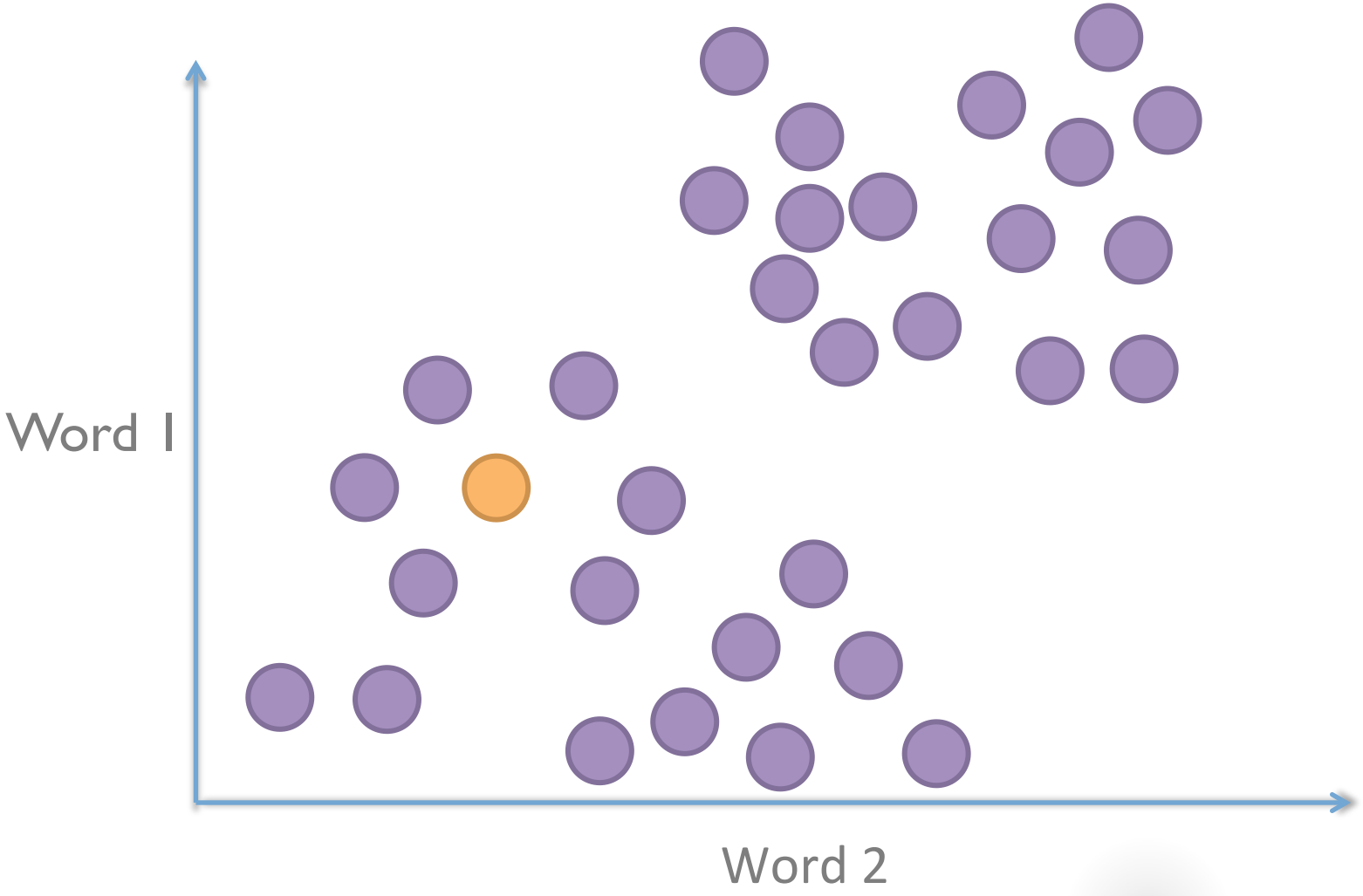
DBSCAN

With cosine distance



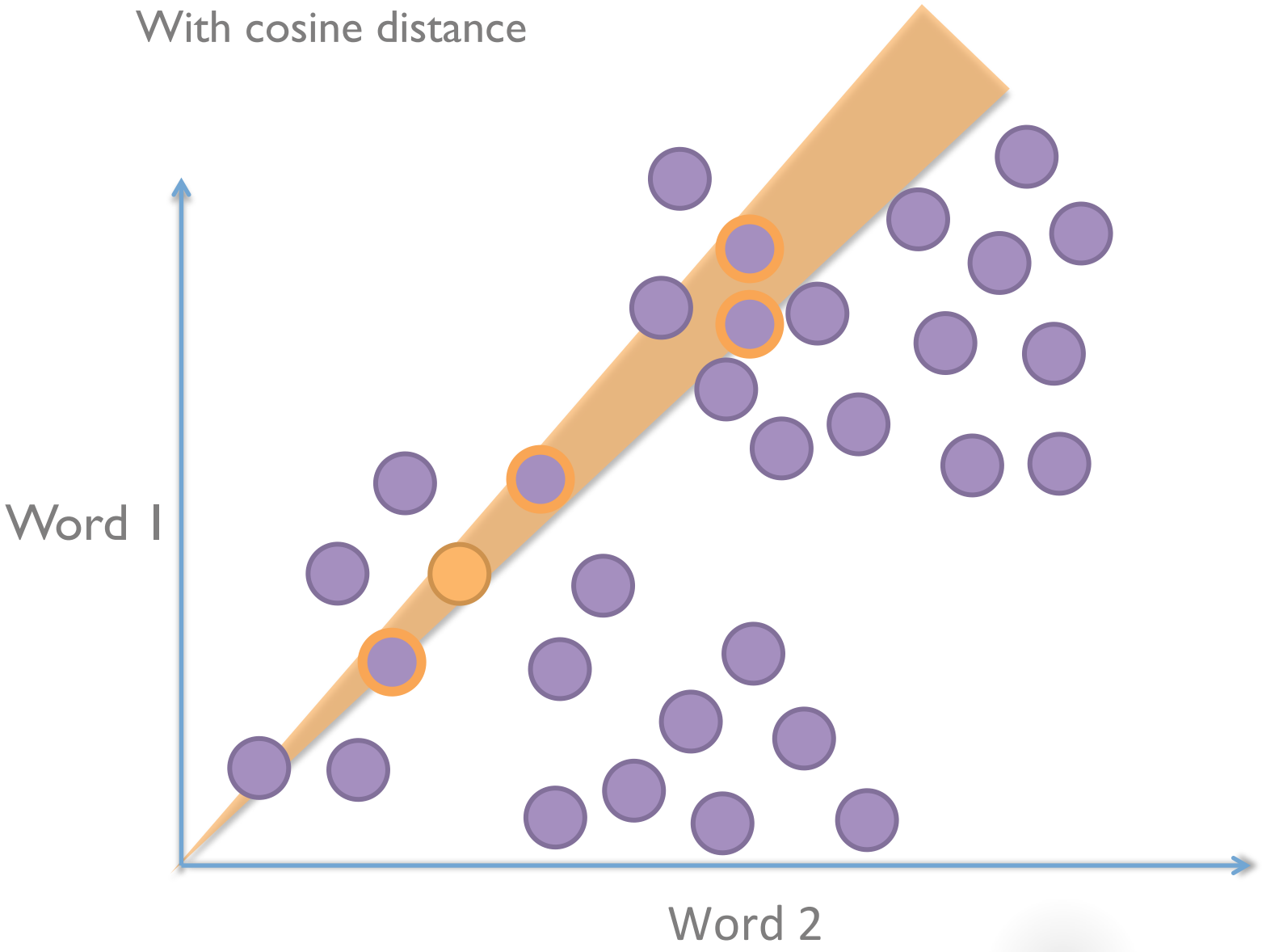
DBSCAN

With cosine distance

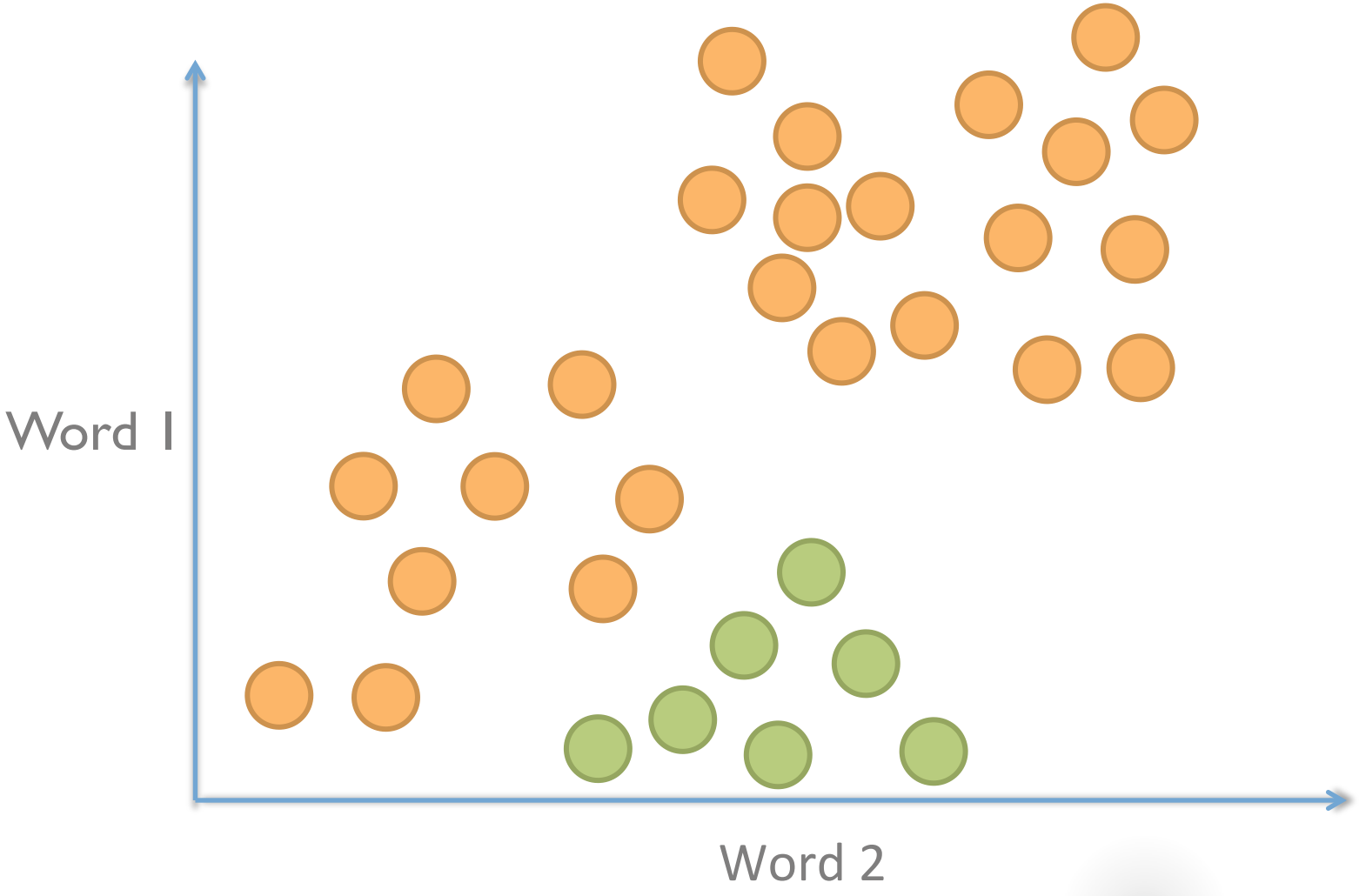


DBSCAN

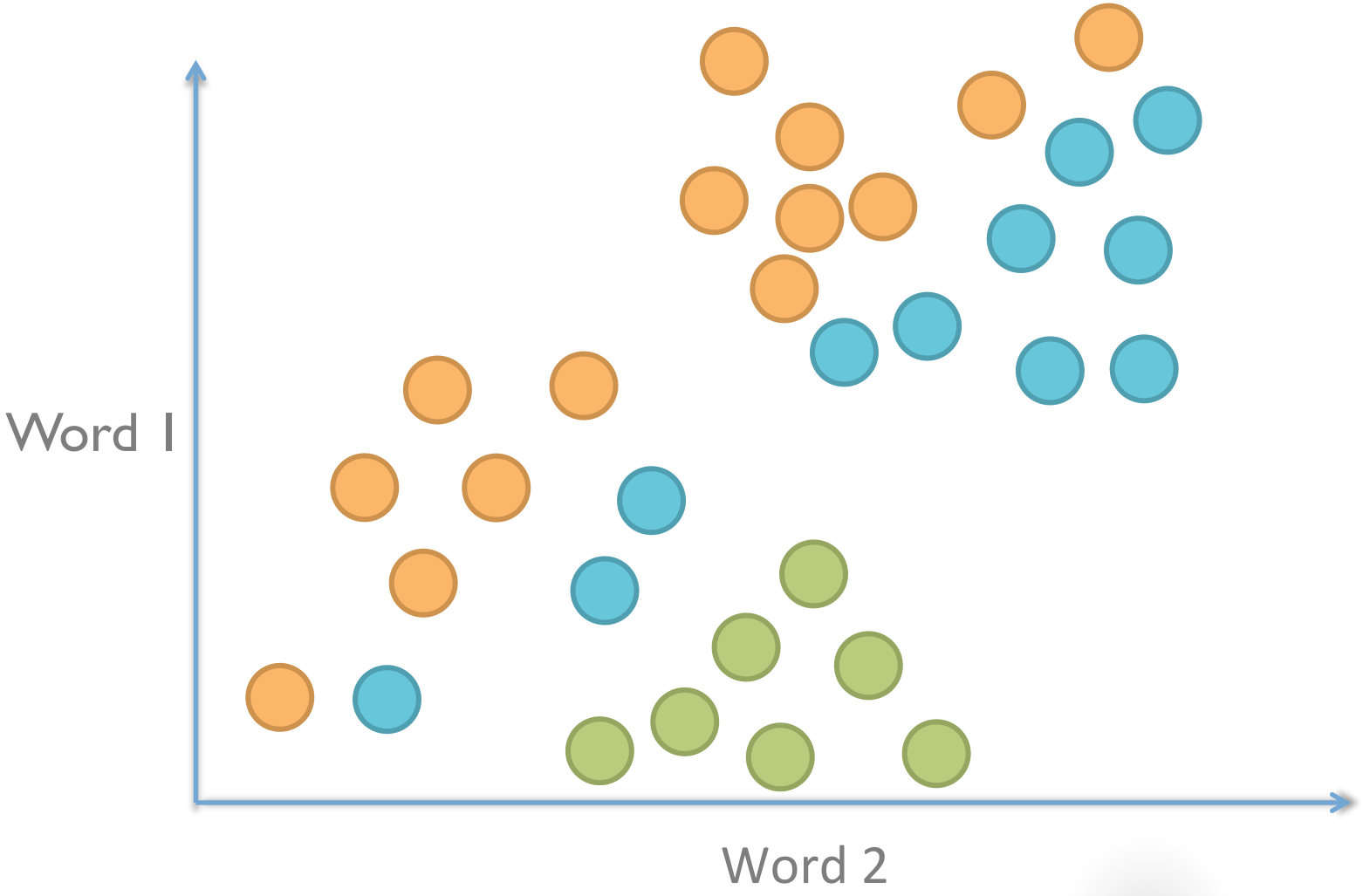
With cosine distance



Potential clusters with cosine distance



Potential clusters with cosine distance



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