Hierarchical Clustering, Topic Modeling

slides by
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Carnegie Mellon University
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Going from Similarities to Clusters

There's a whole zoo of clustering methods

Two main categories we'll talk about:

Generative models

1. Pretend data generated by specific model with parameters

2. Learn the parameters ("fit model to data")

3. Use fitted model to determine cluster assignments

Hierarchical clustering

Top-down: Start with everything in 1 cluster and decide on how to recursively split

Bottom-up: Start with everything in its own cluster and decide on how to iteratively merge clusters

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Divisive Clustering

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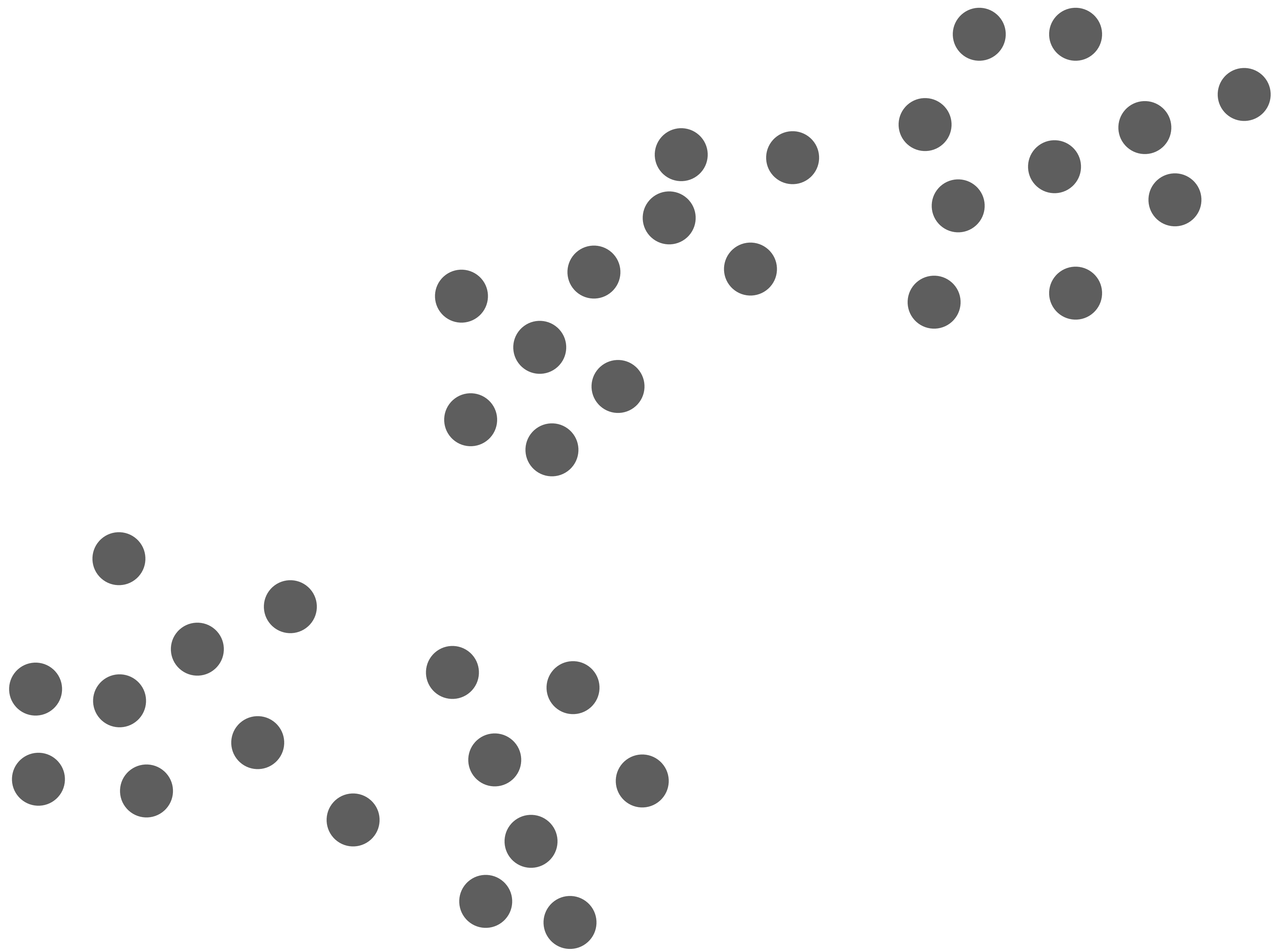
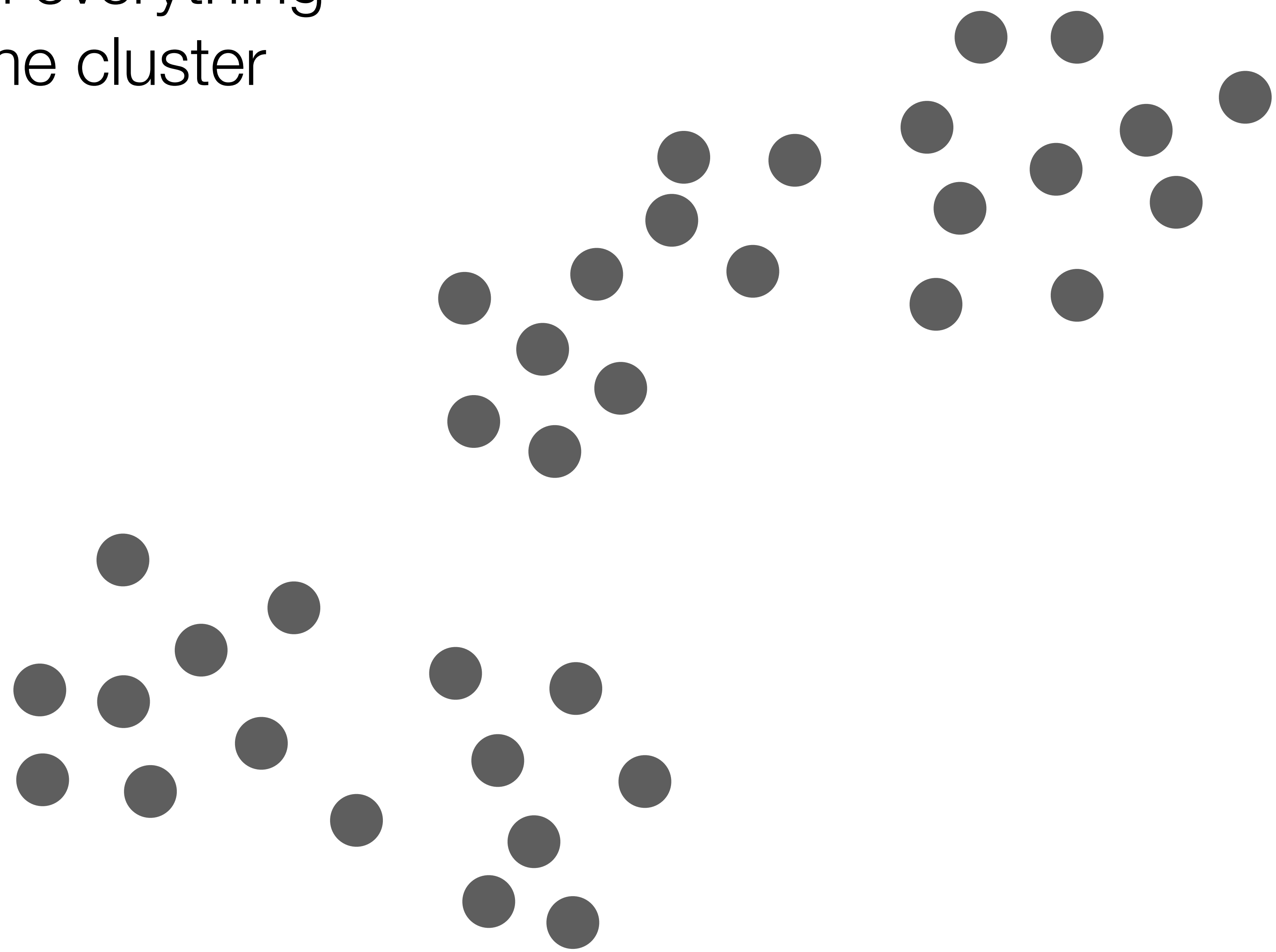


Divisive Clustering

0. Start with everything
   in the same cluster



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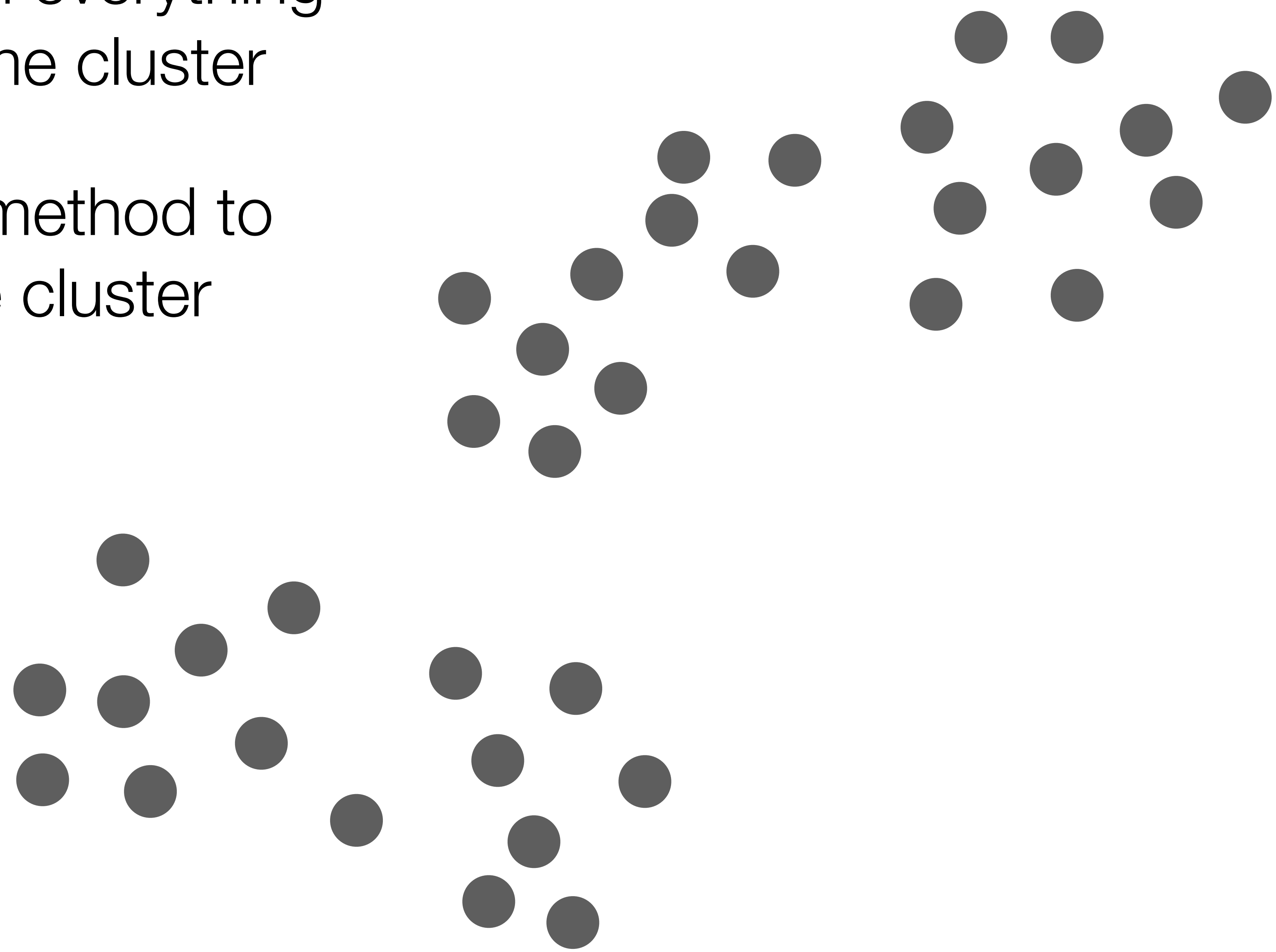

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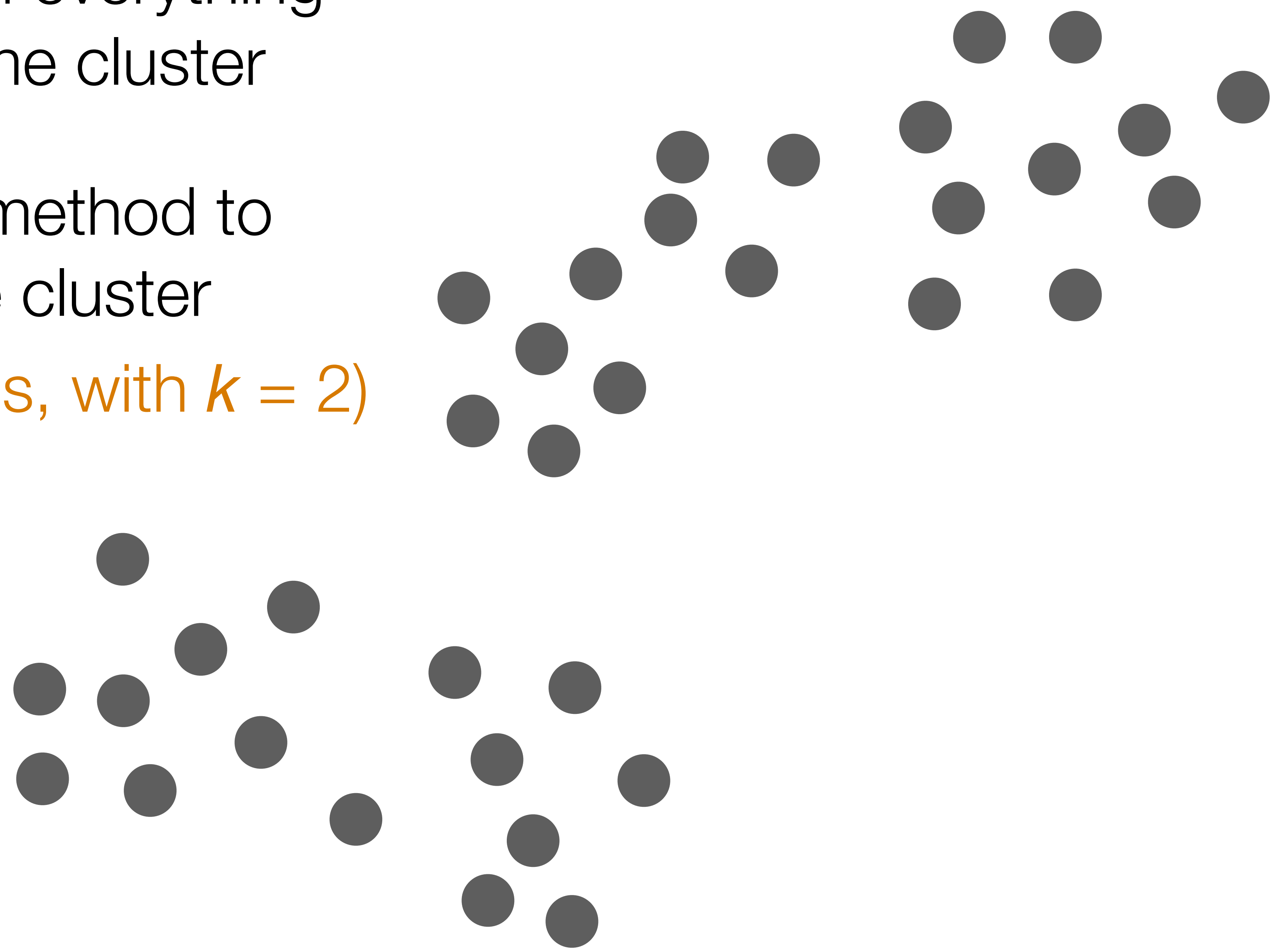
(e.g., k-means, with k = 2)



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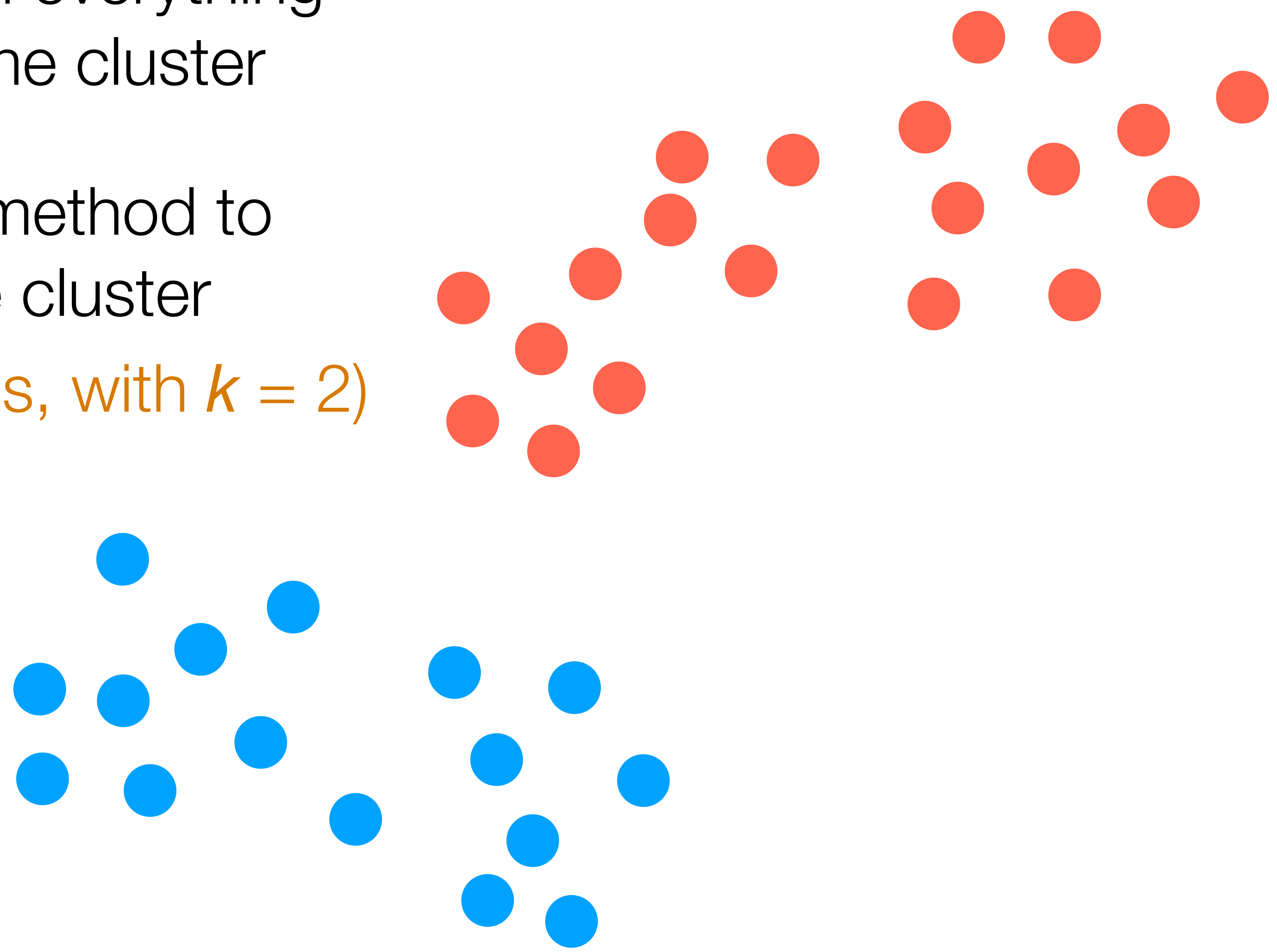

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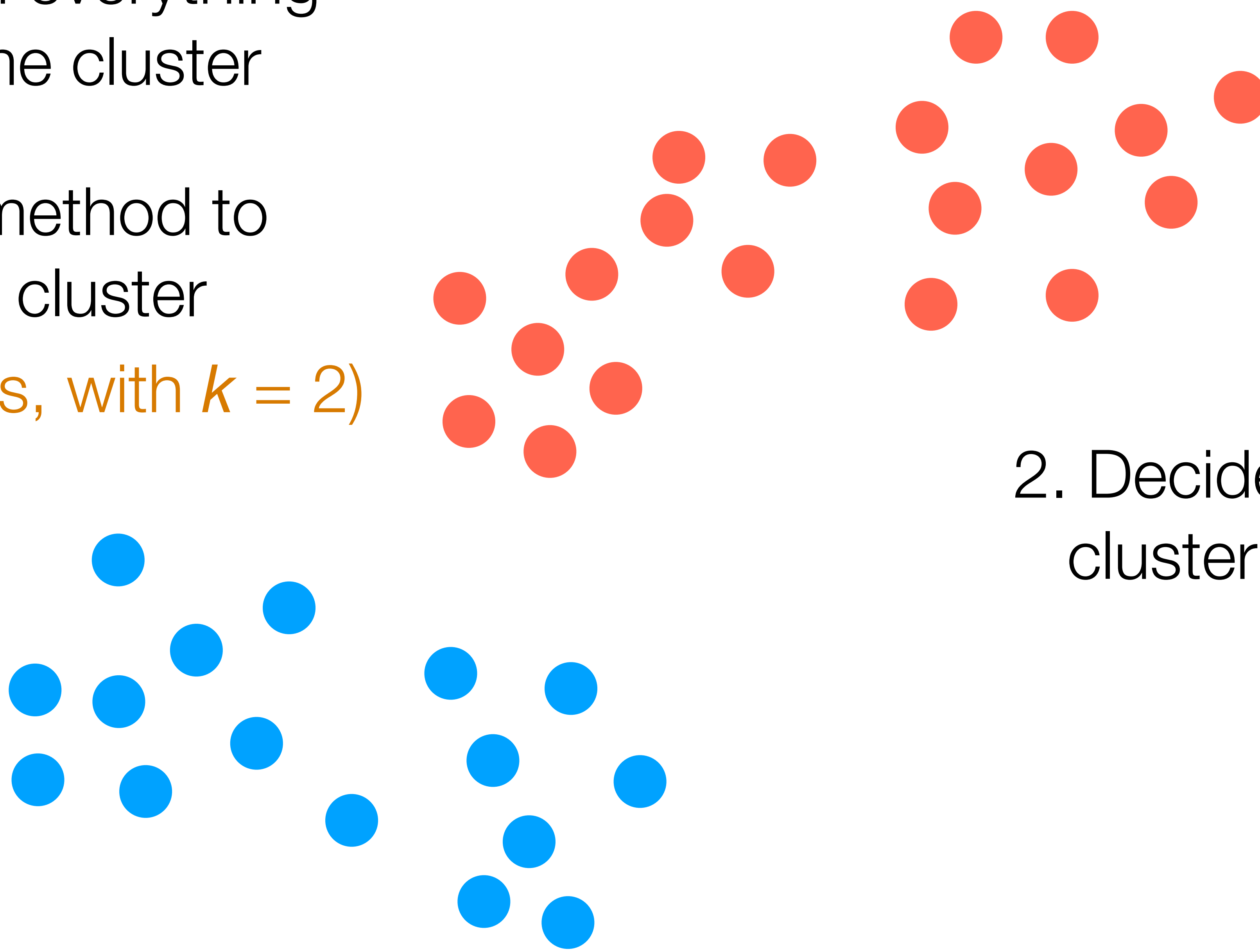

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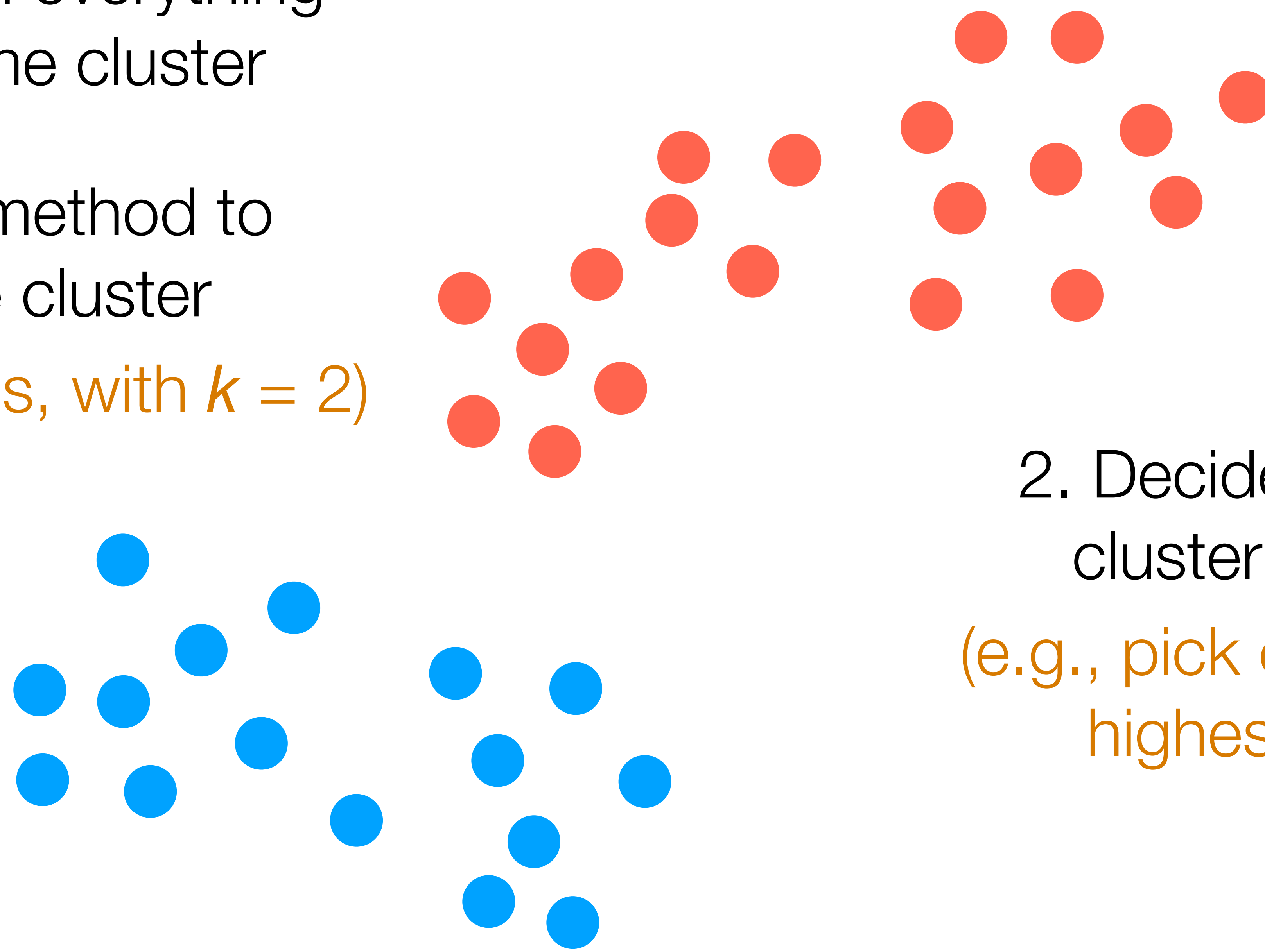

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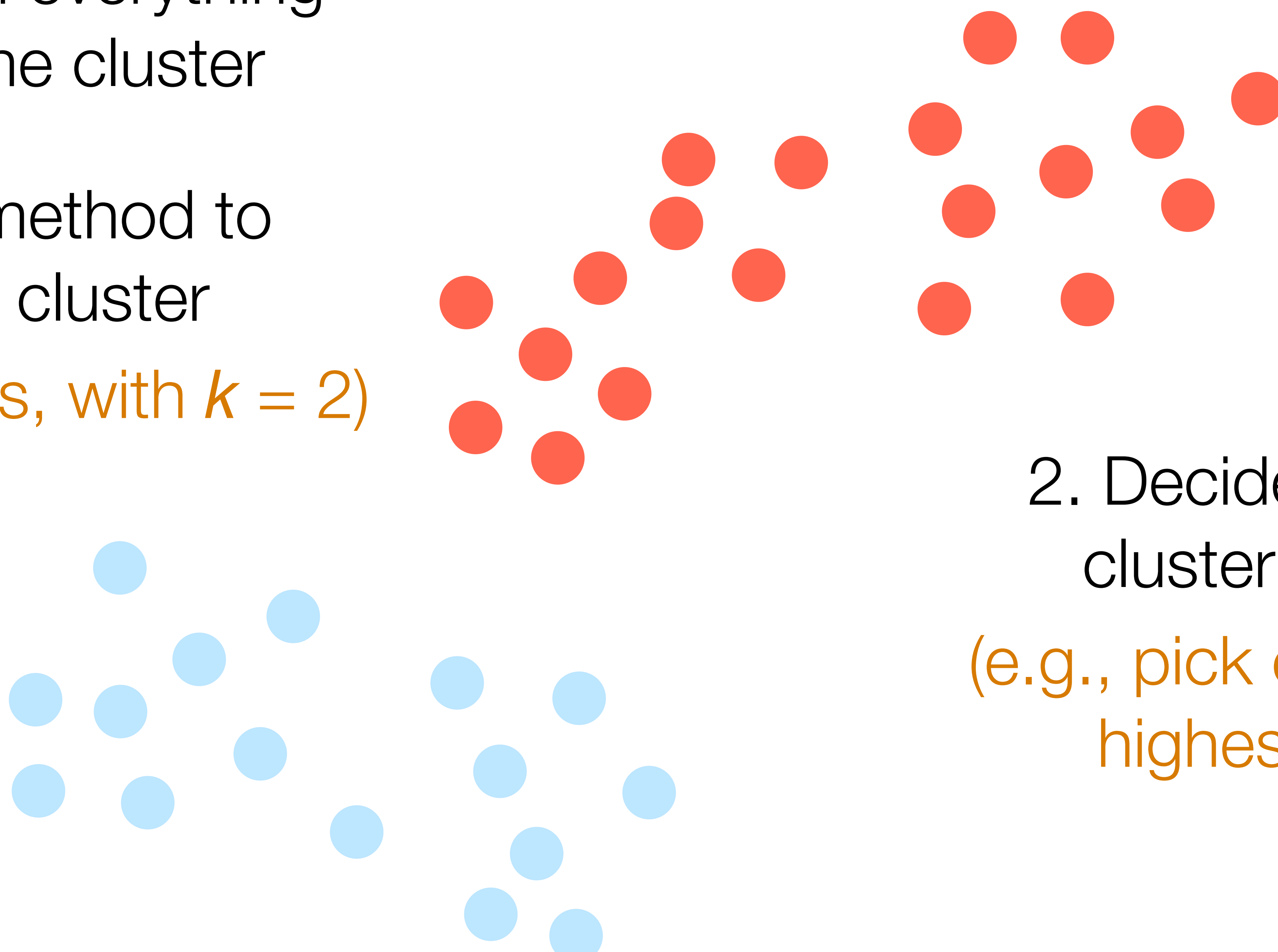

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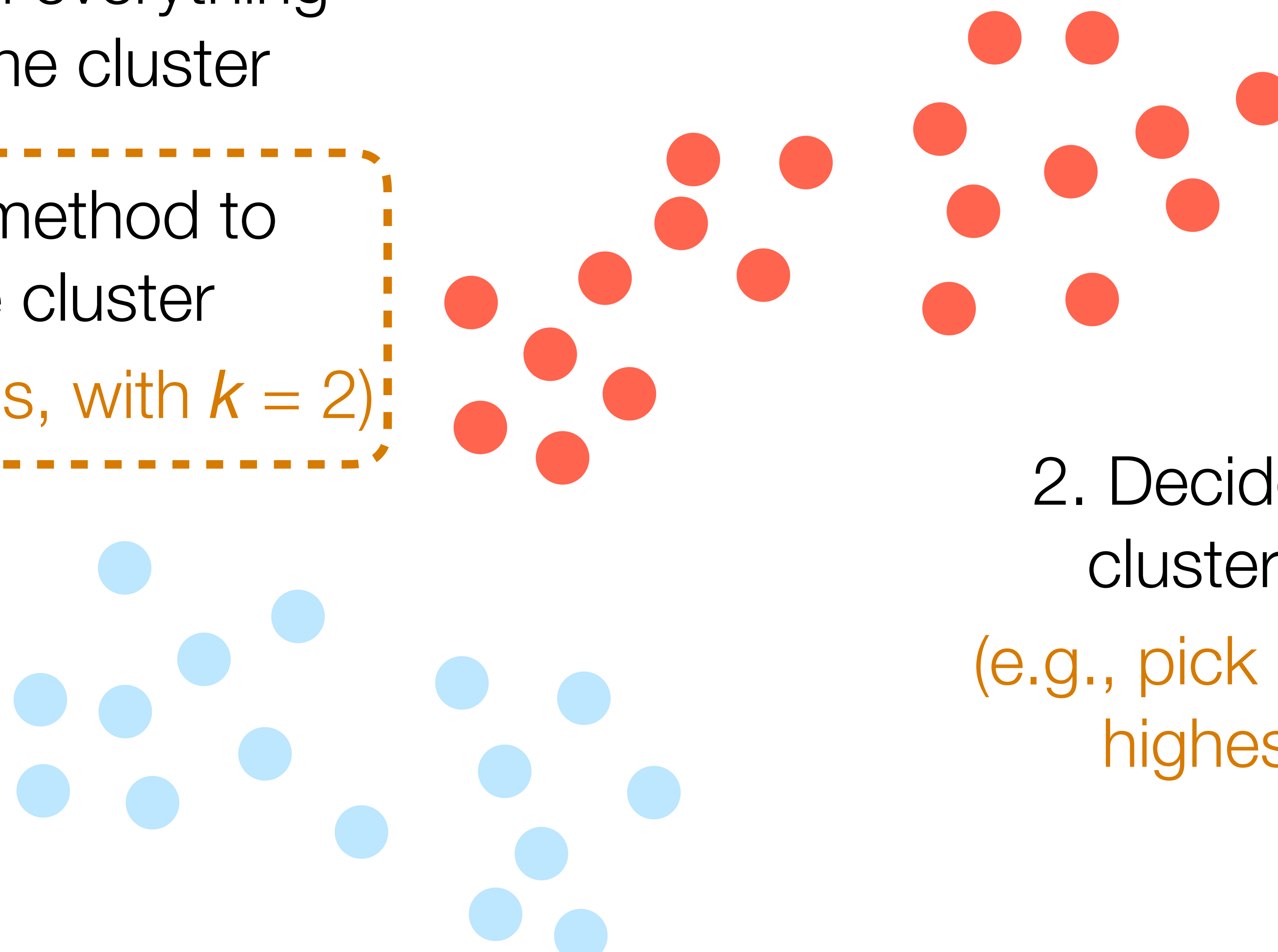

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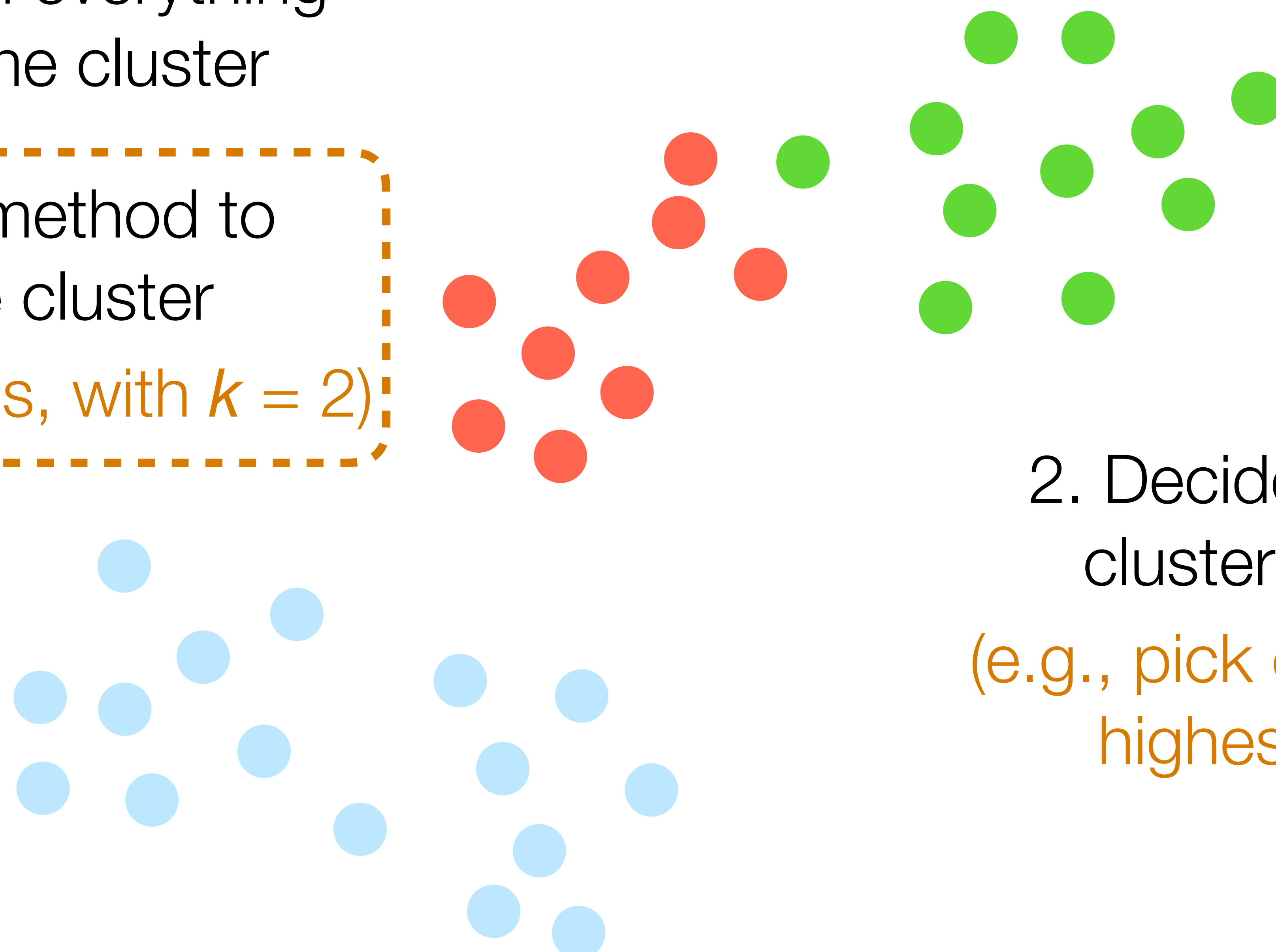

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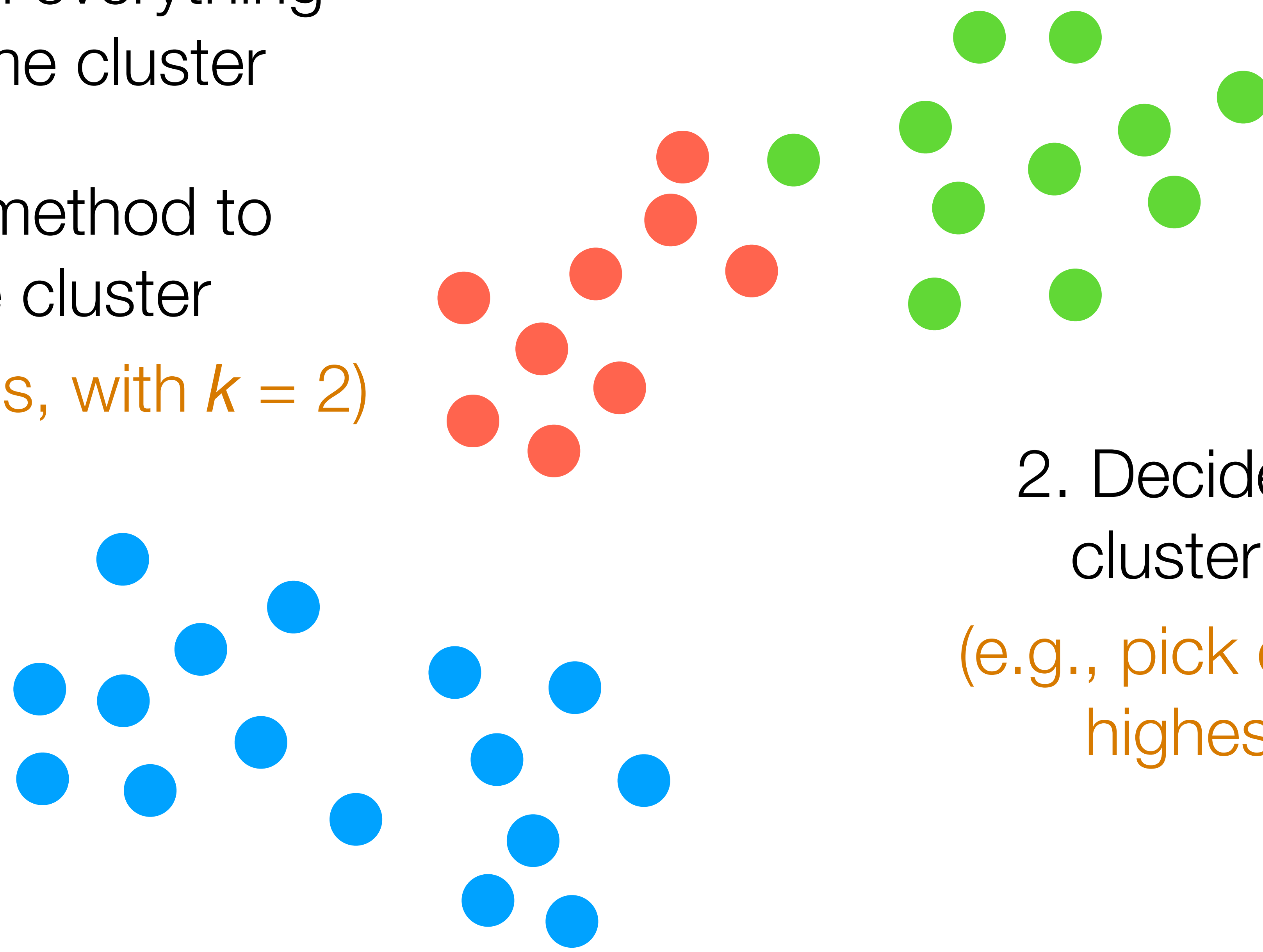

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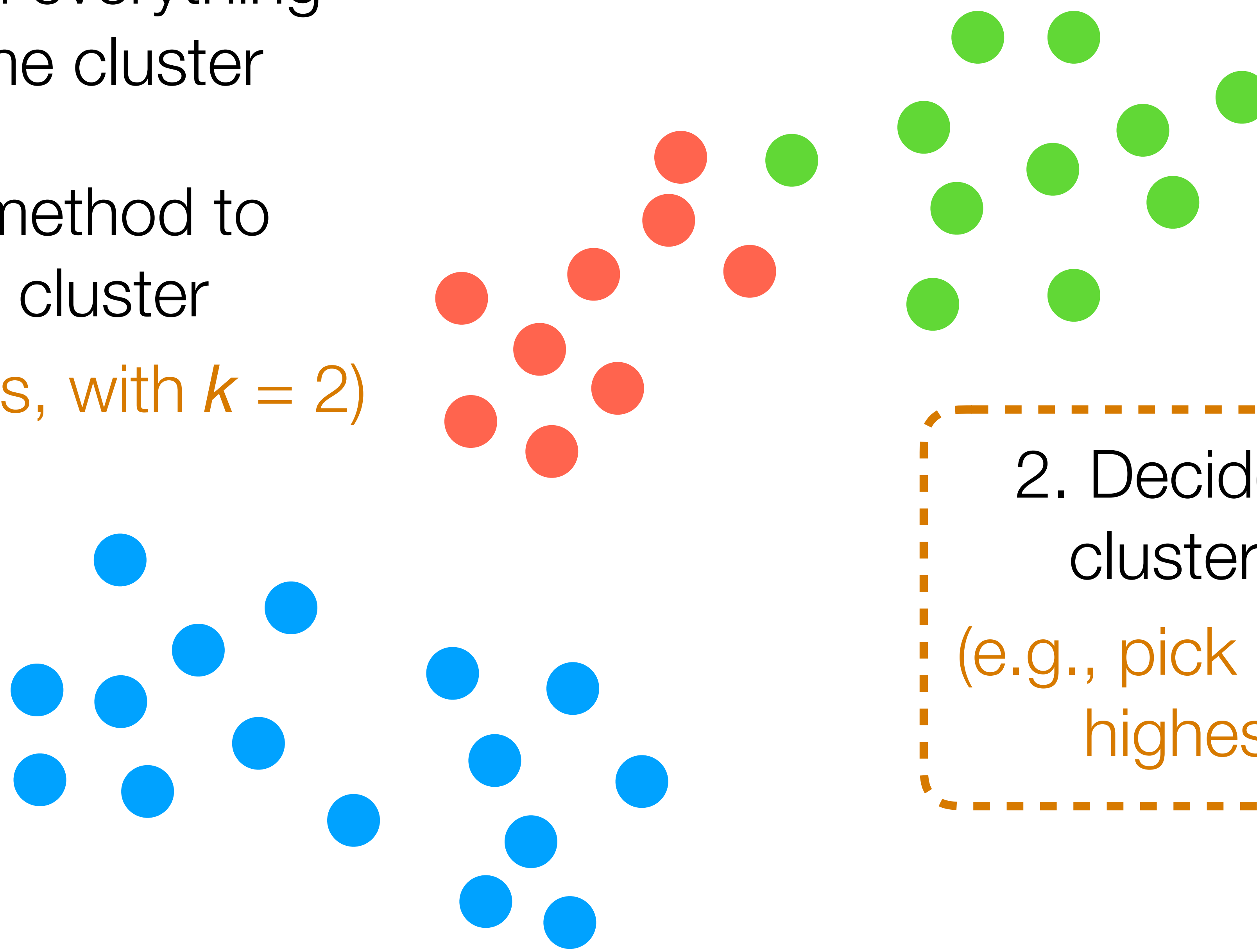

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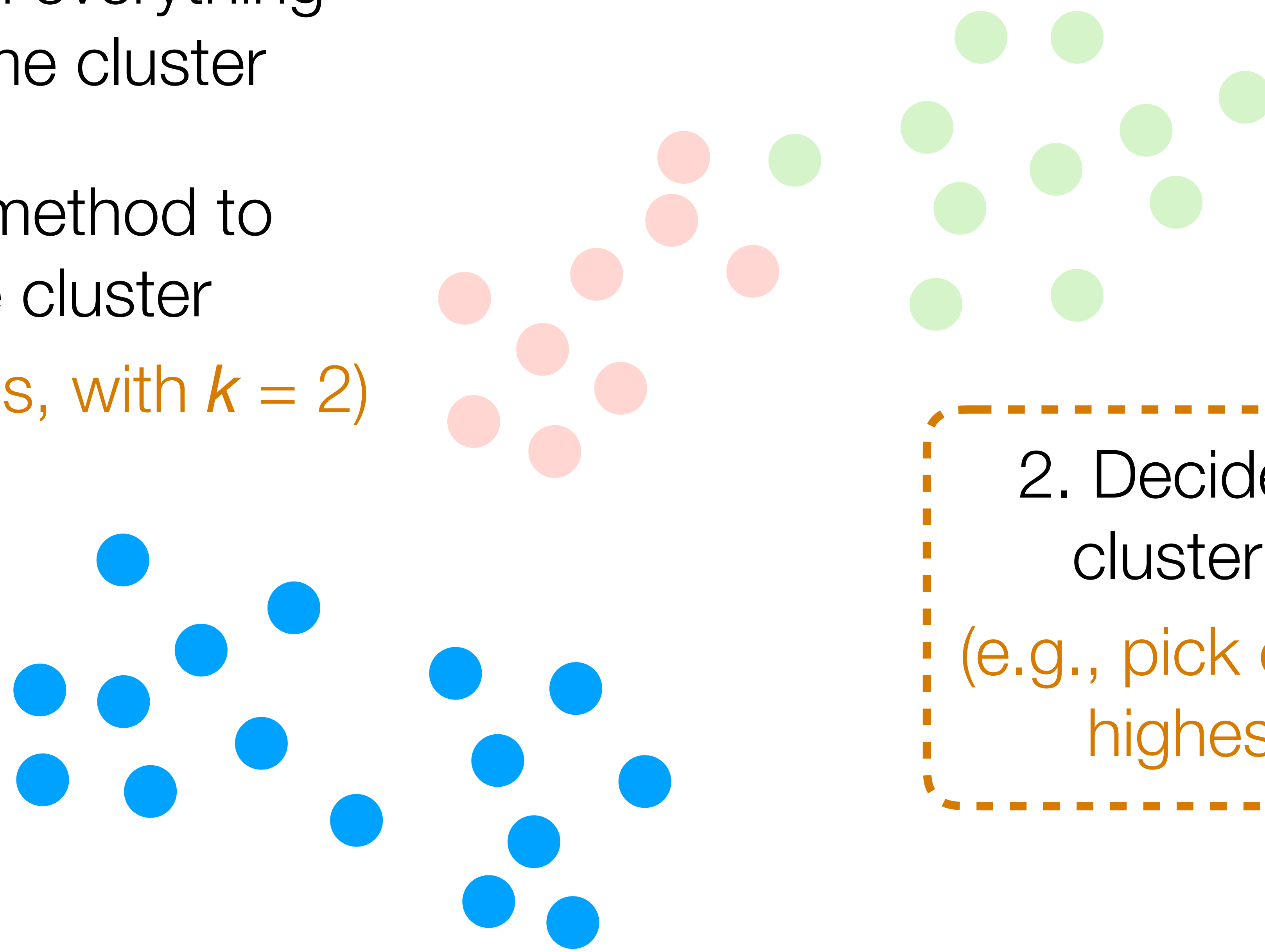

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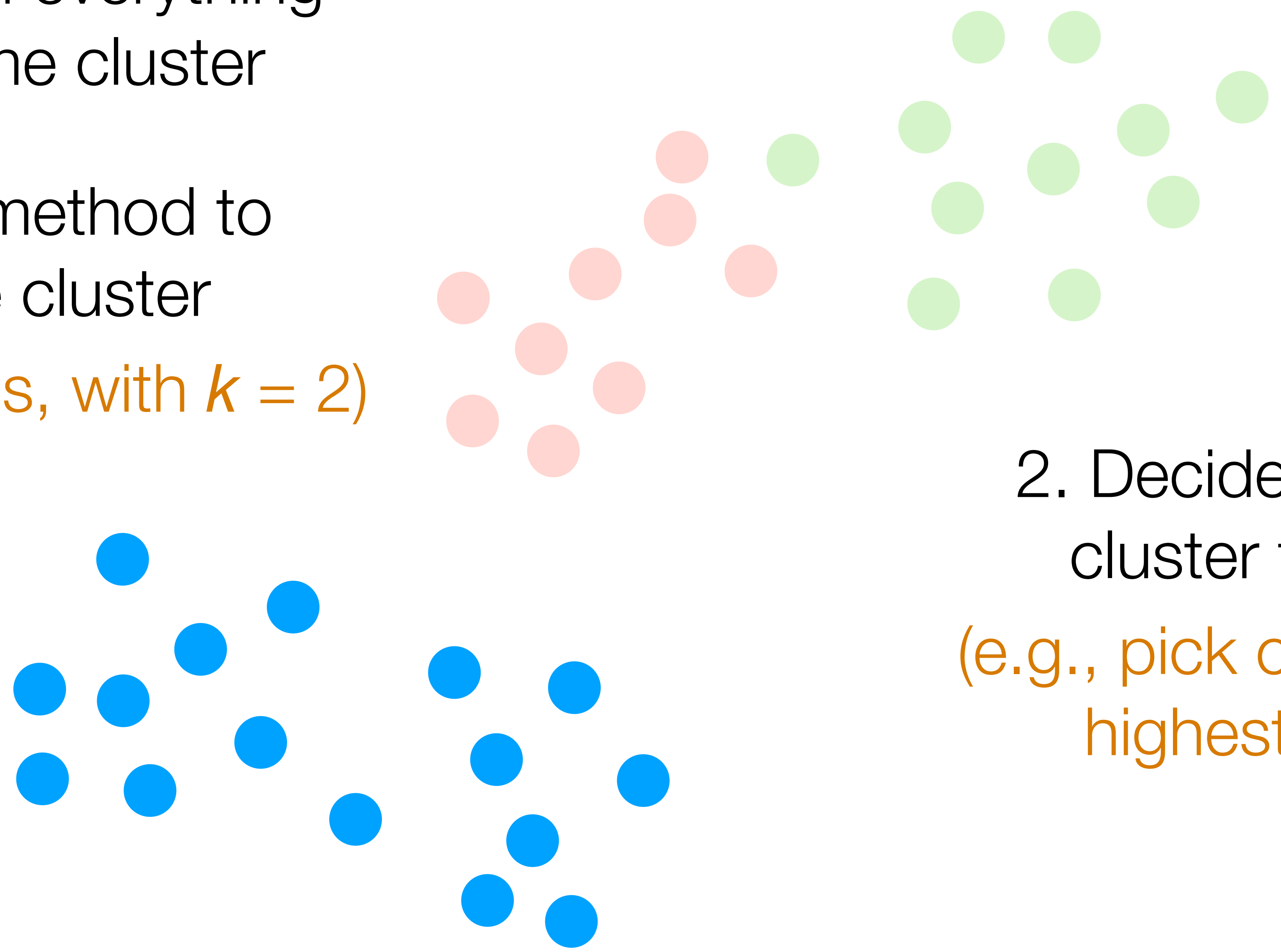

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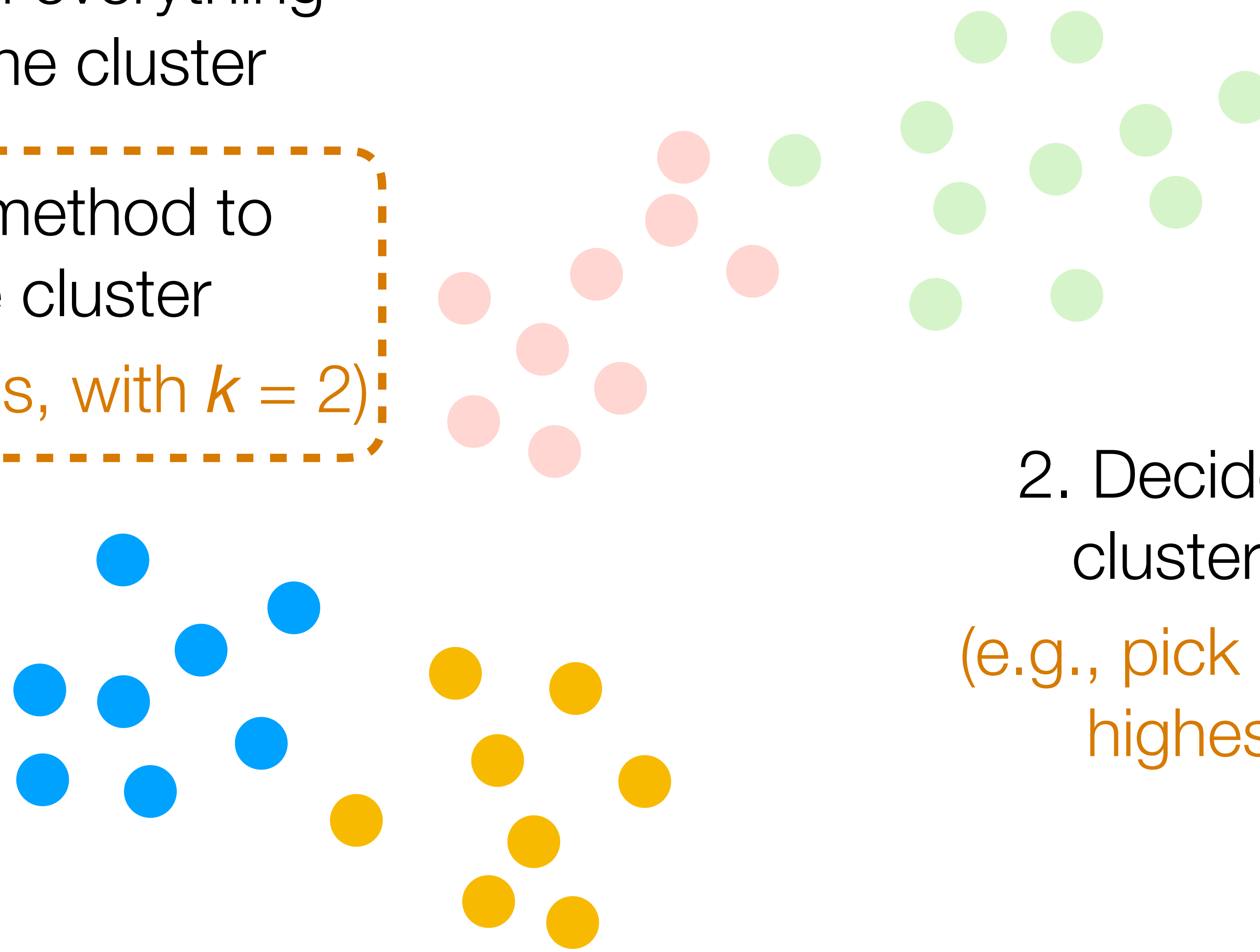

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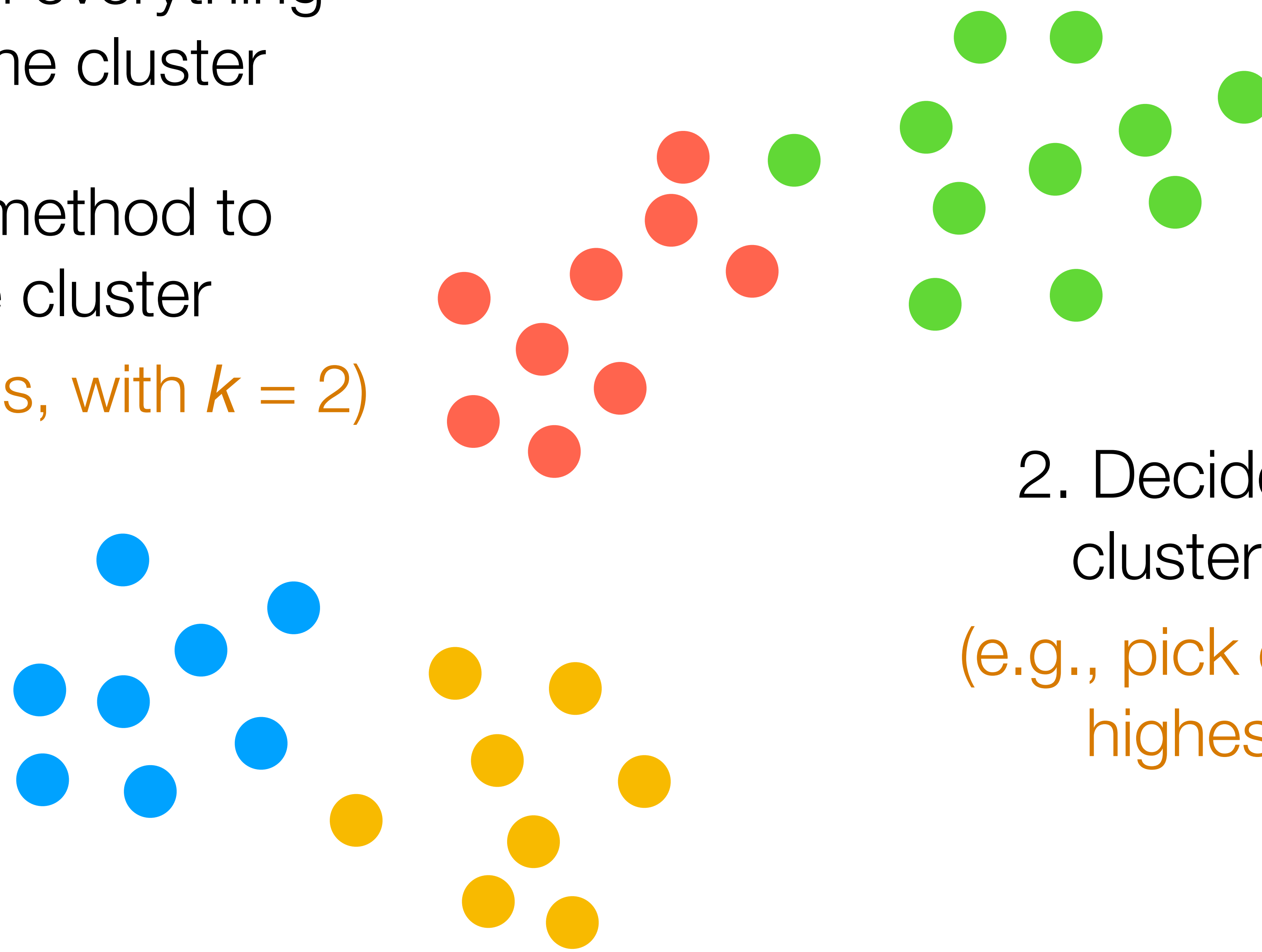

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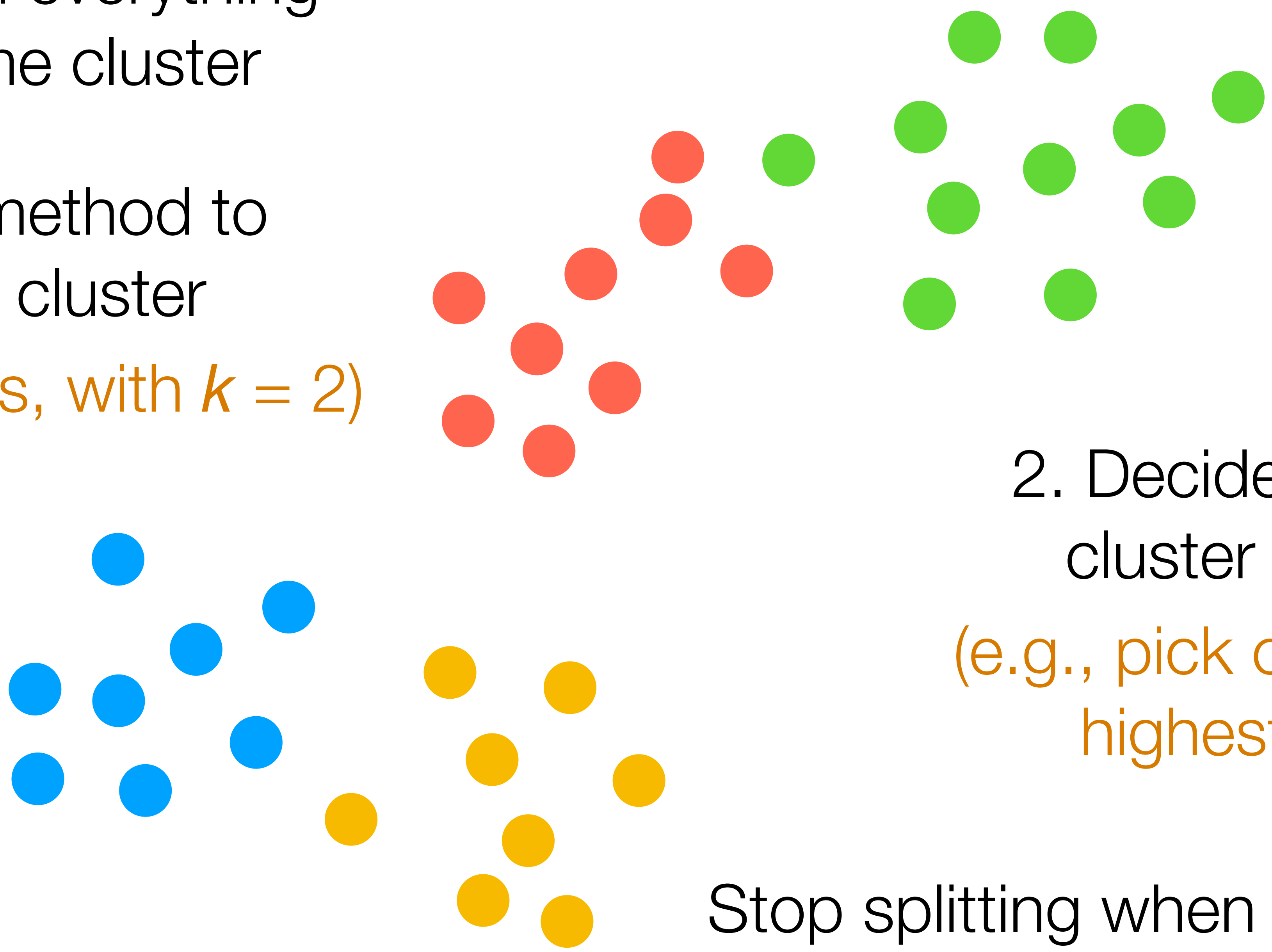

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Stop splitting when some termination condition is reached

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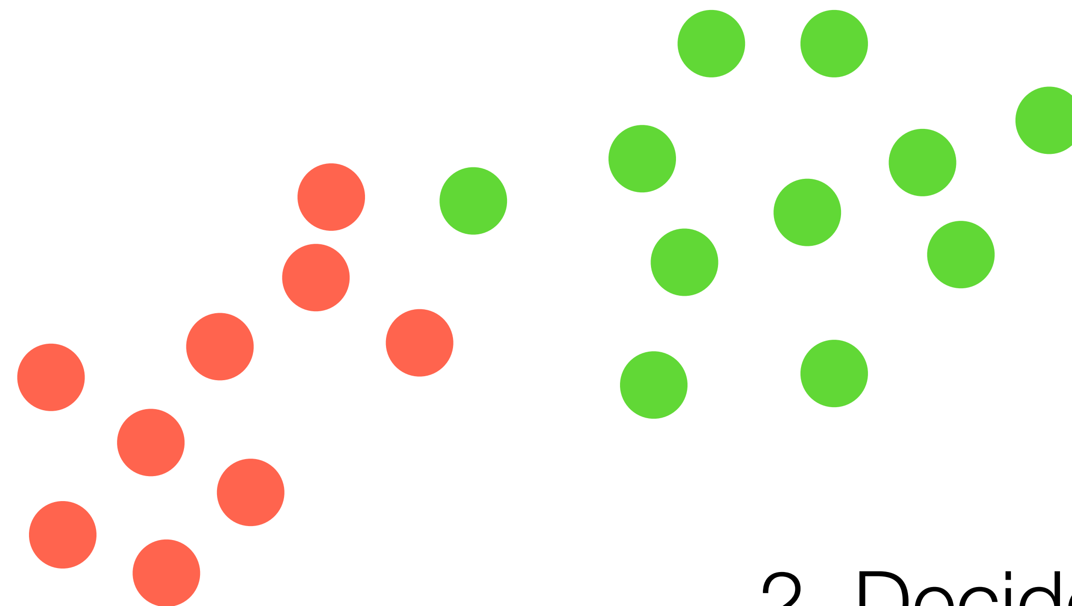

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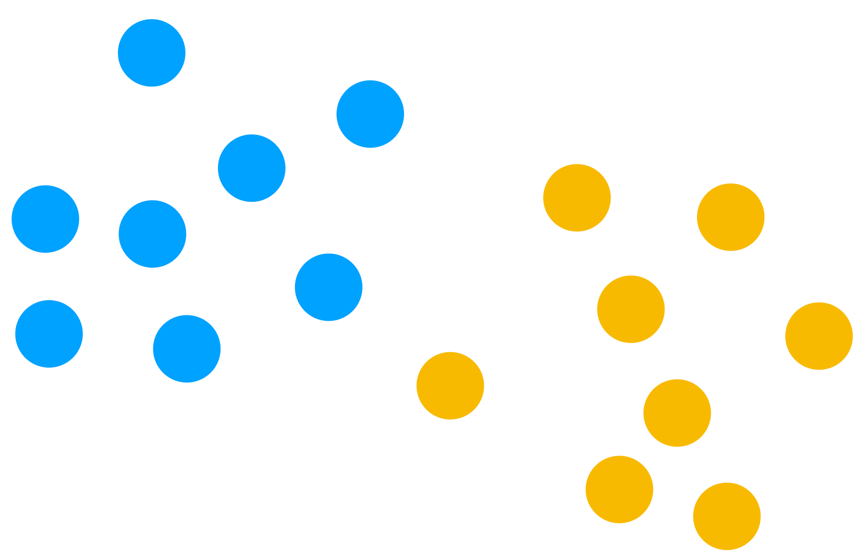

Stop splitting when some termination condition is reached
(e.g., highest cluster RSS is small enough)

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We can view the process in terms of a tree (colors are *not* important here and just help relate to the previous slide)

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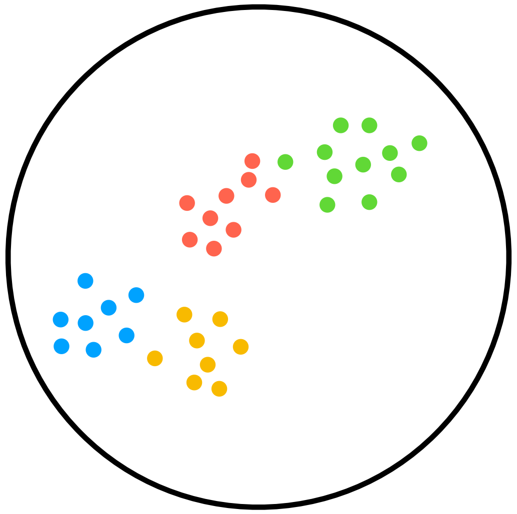

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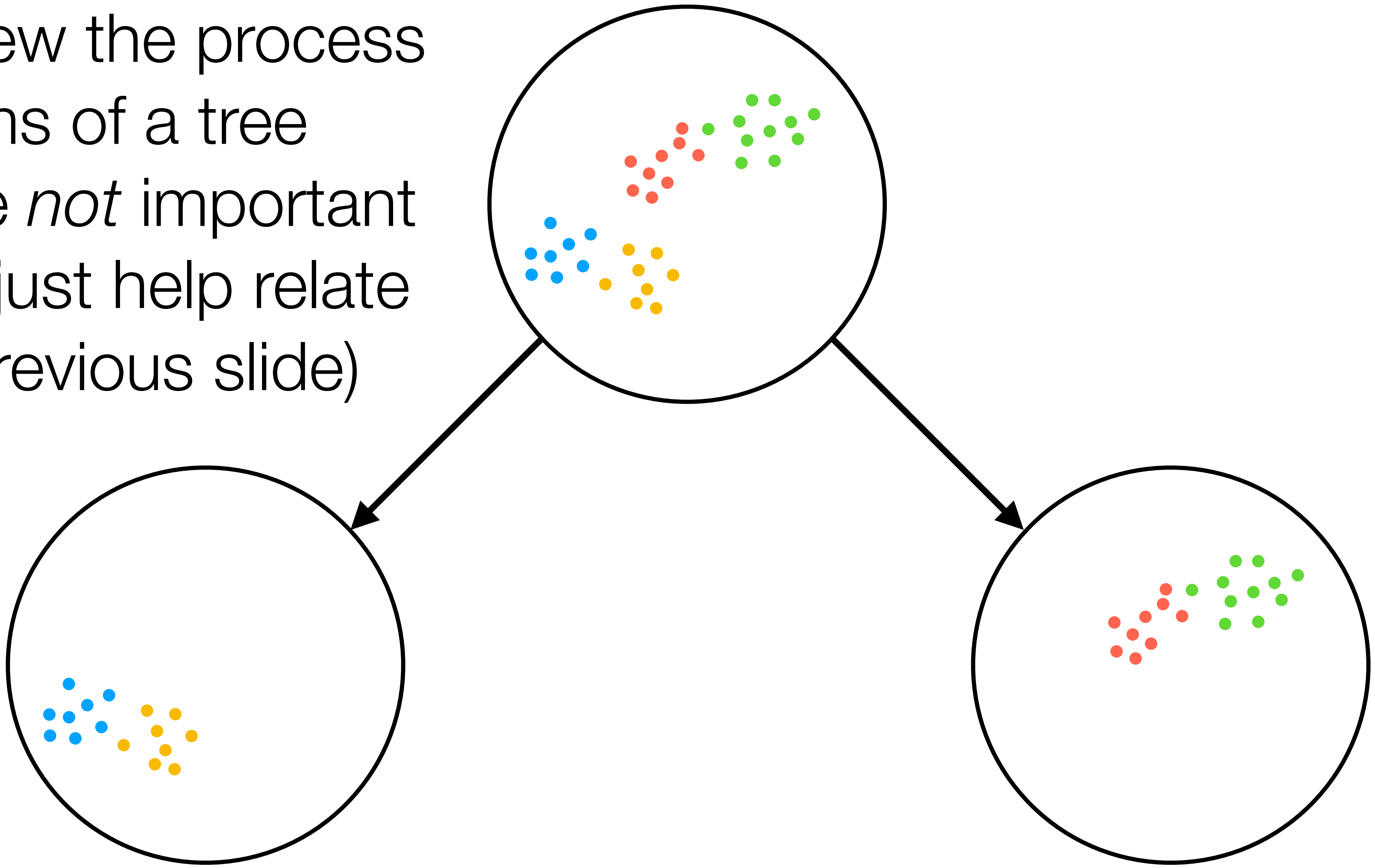

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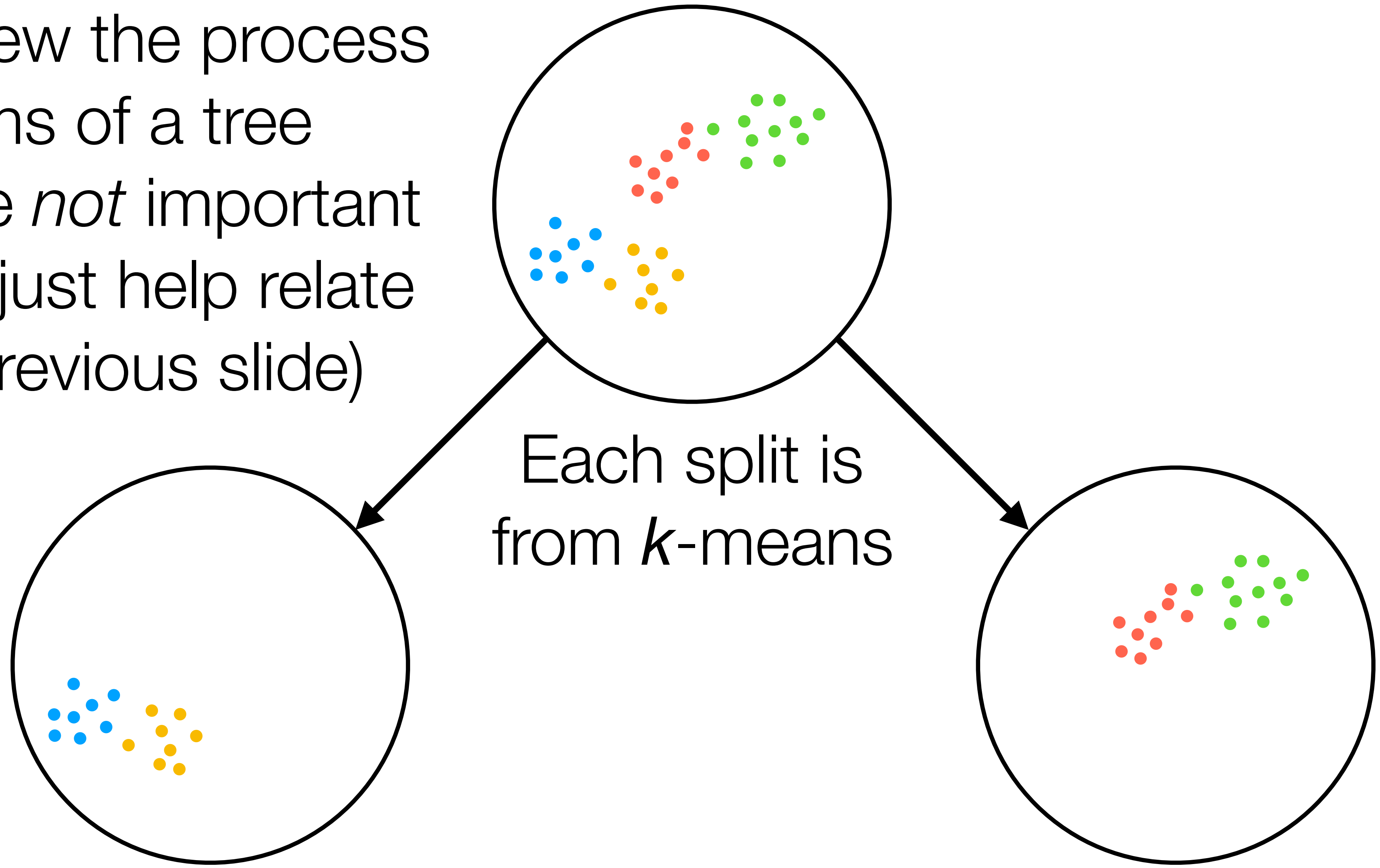

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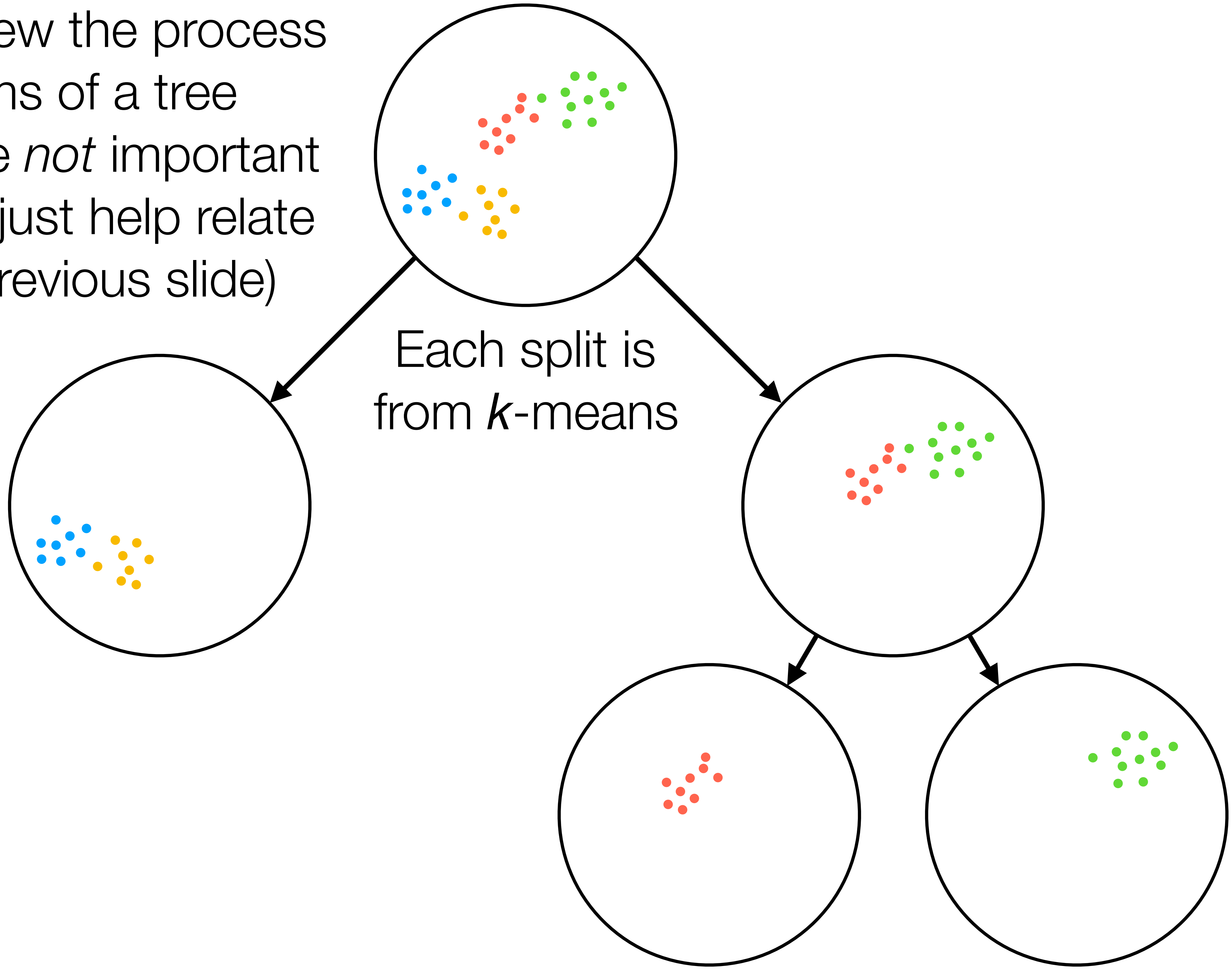

Each split is from *k*-means

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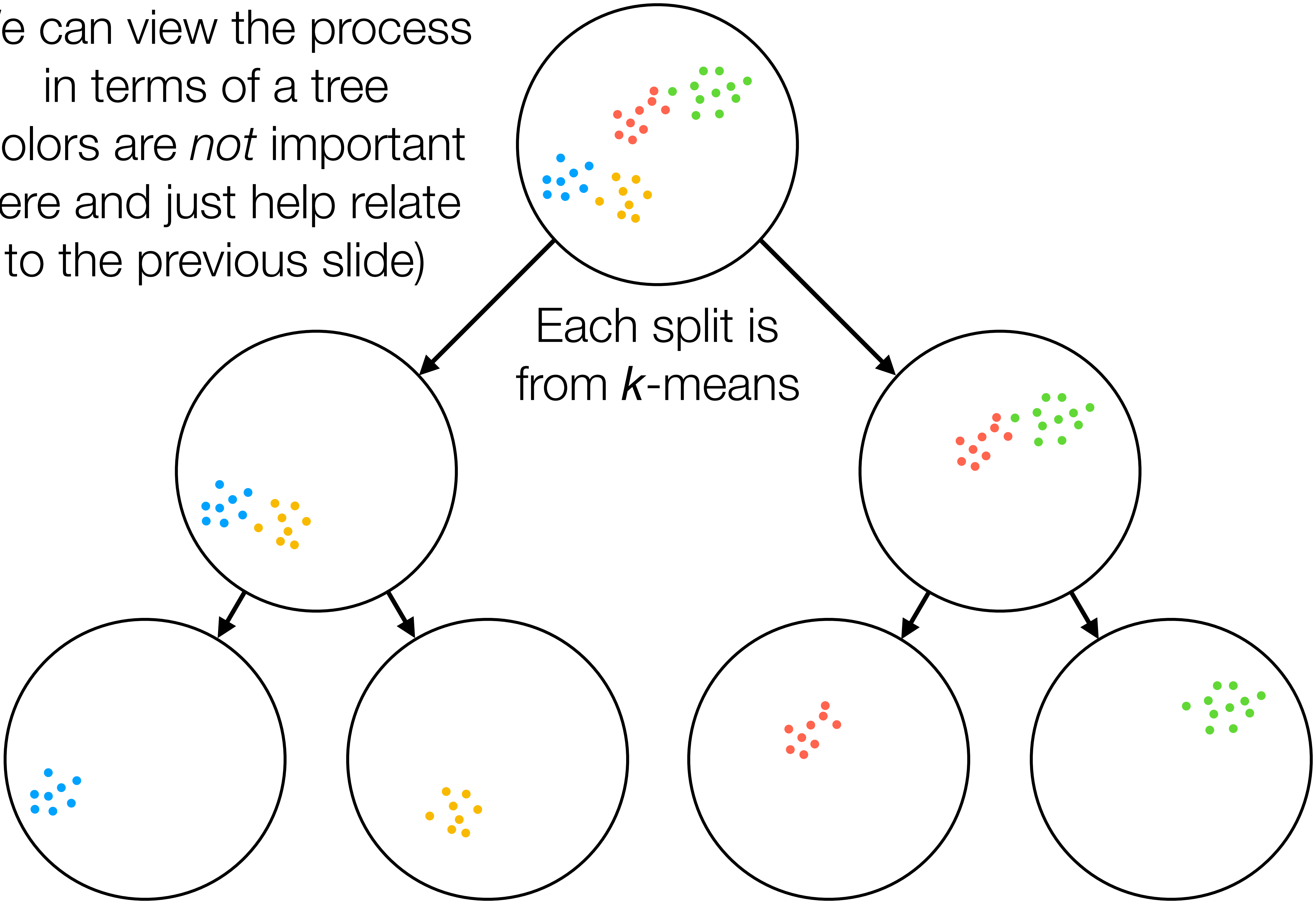

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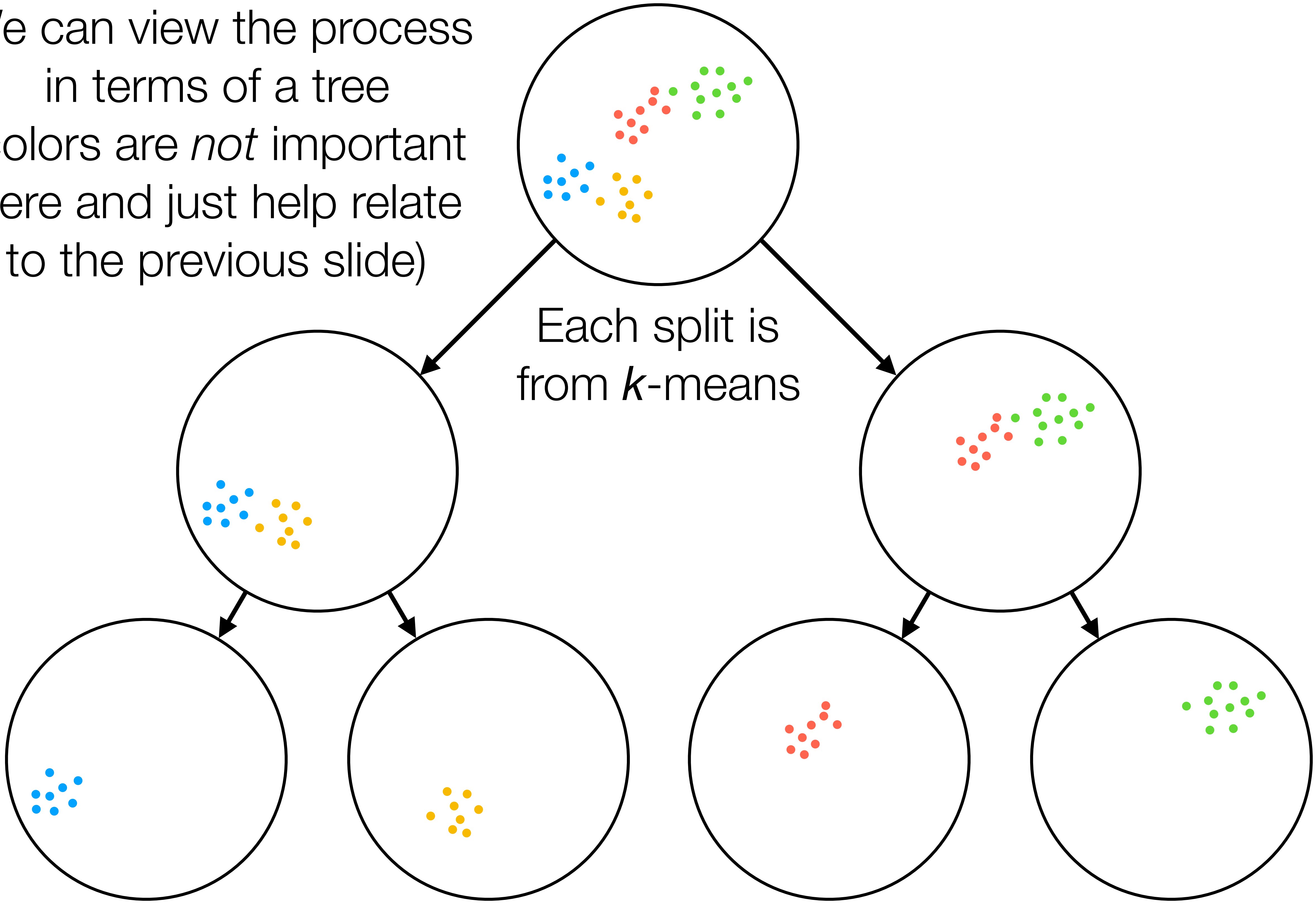

We could keep splitting until the leaves each have 1 point

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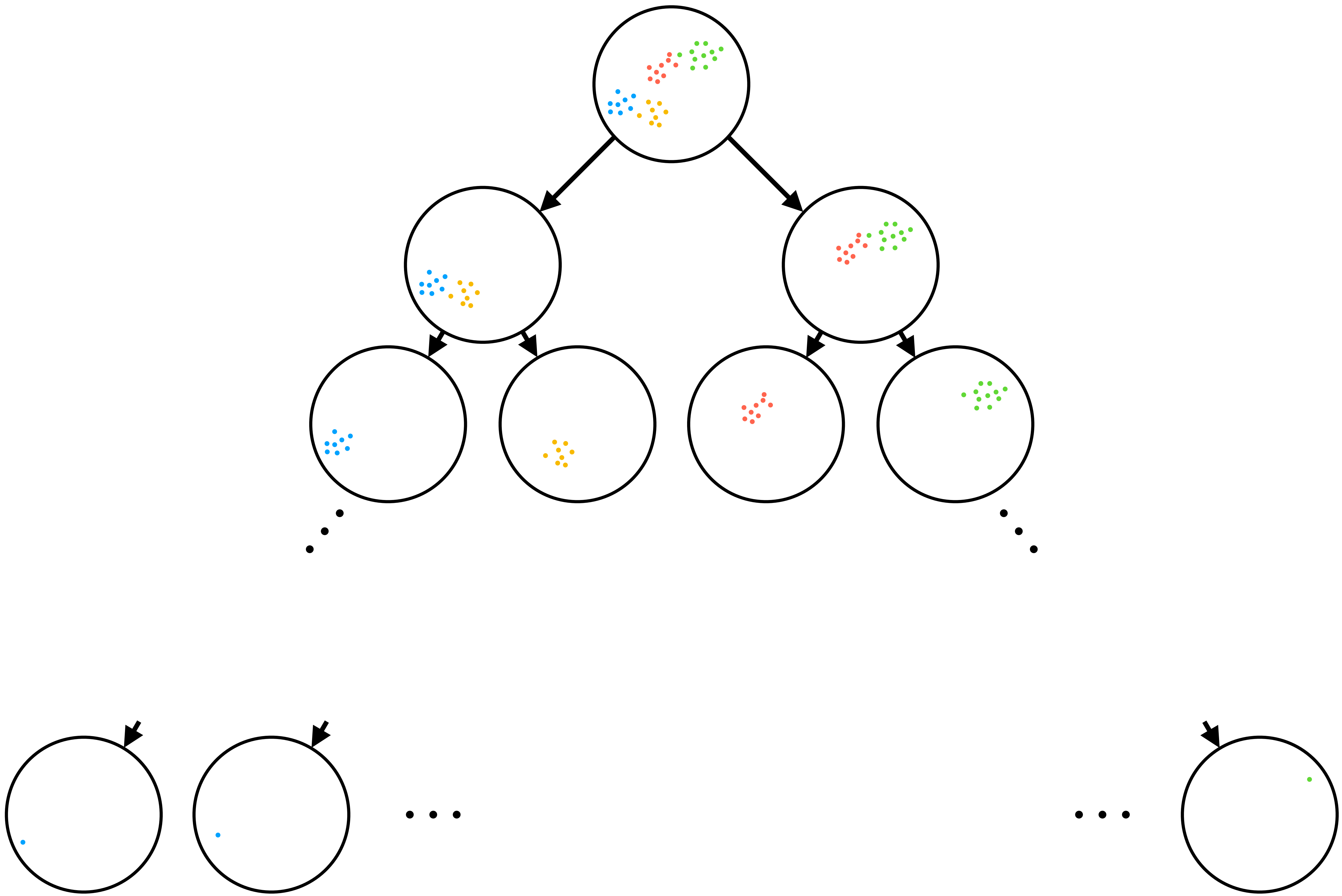

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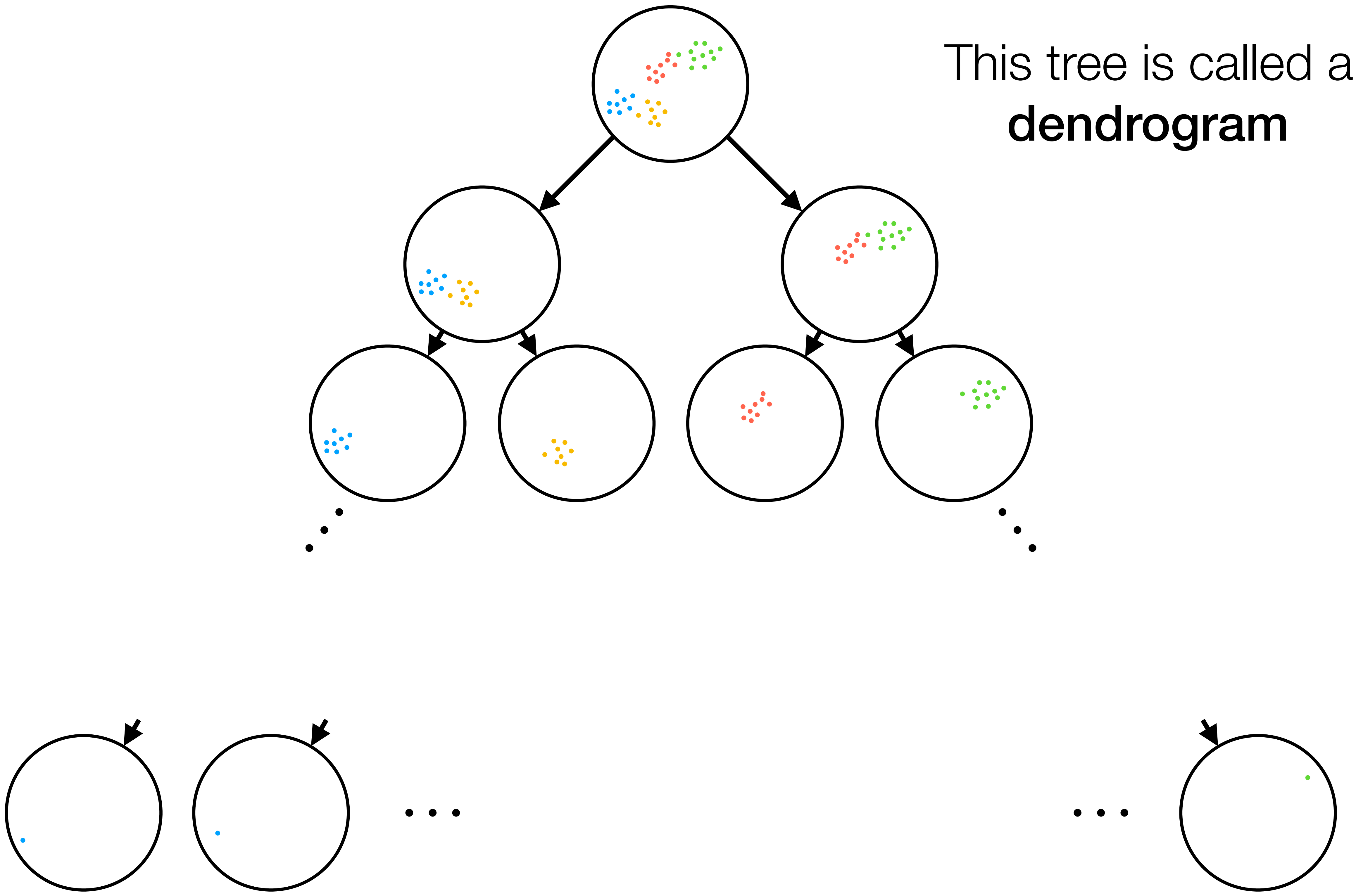

This tree is called a **dendrogram**

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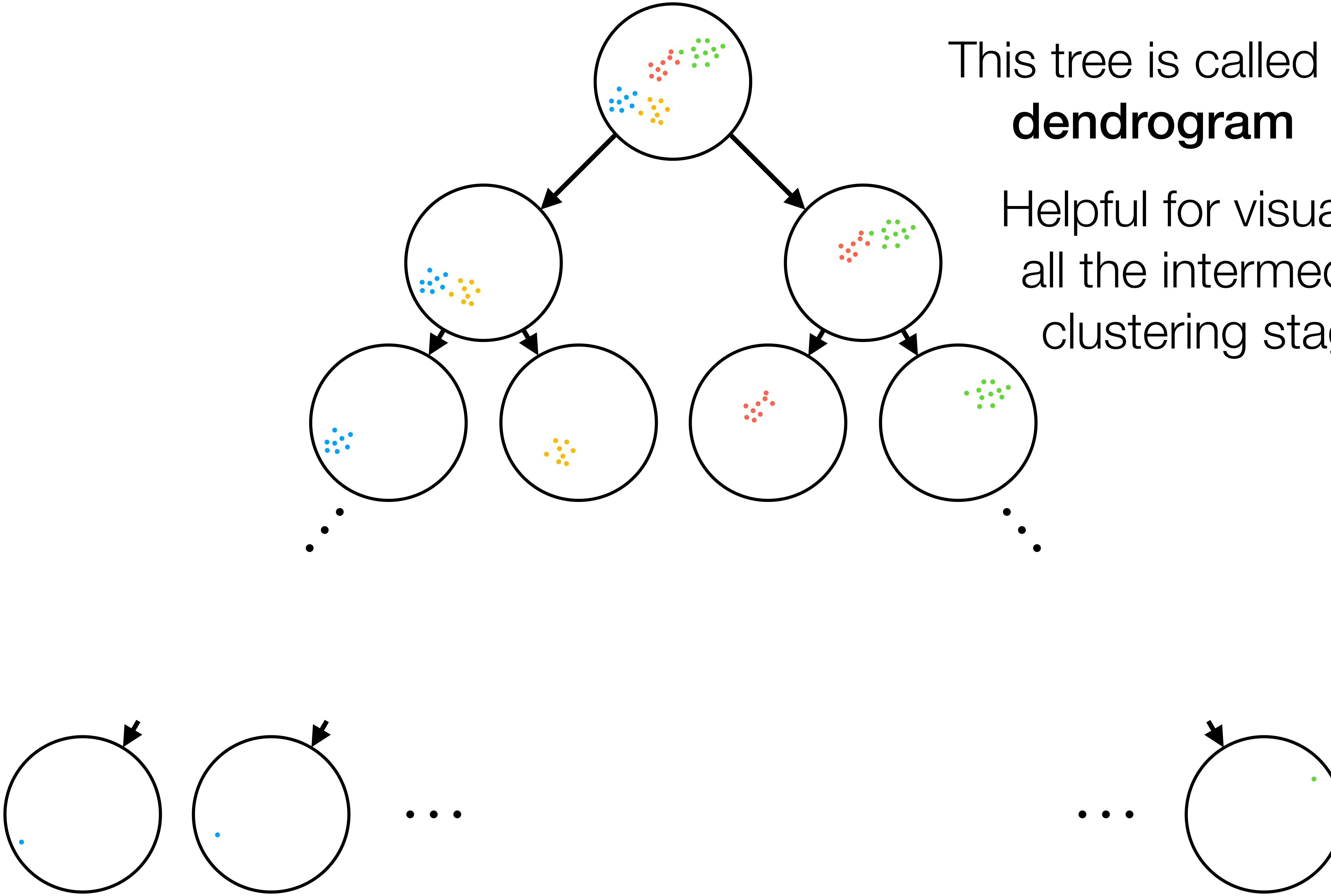

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Helpful for visualizing all the intermediate clustering stages

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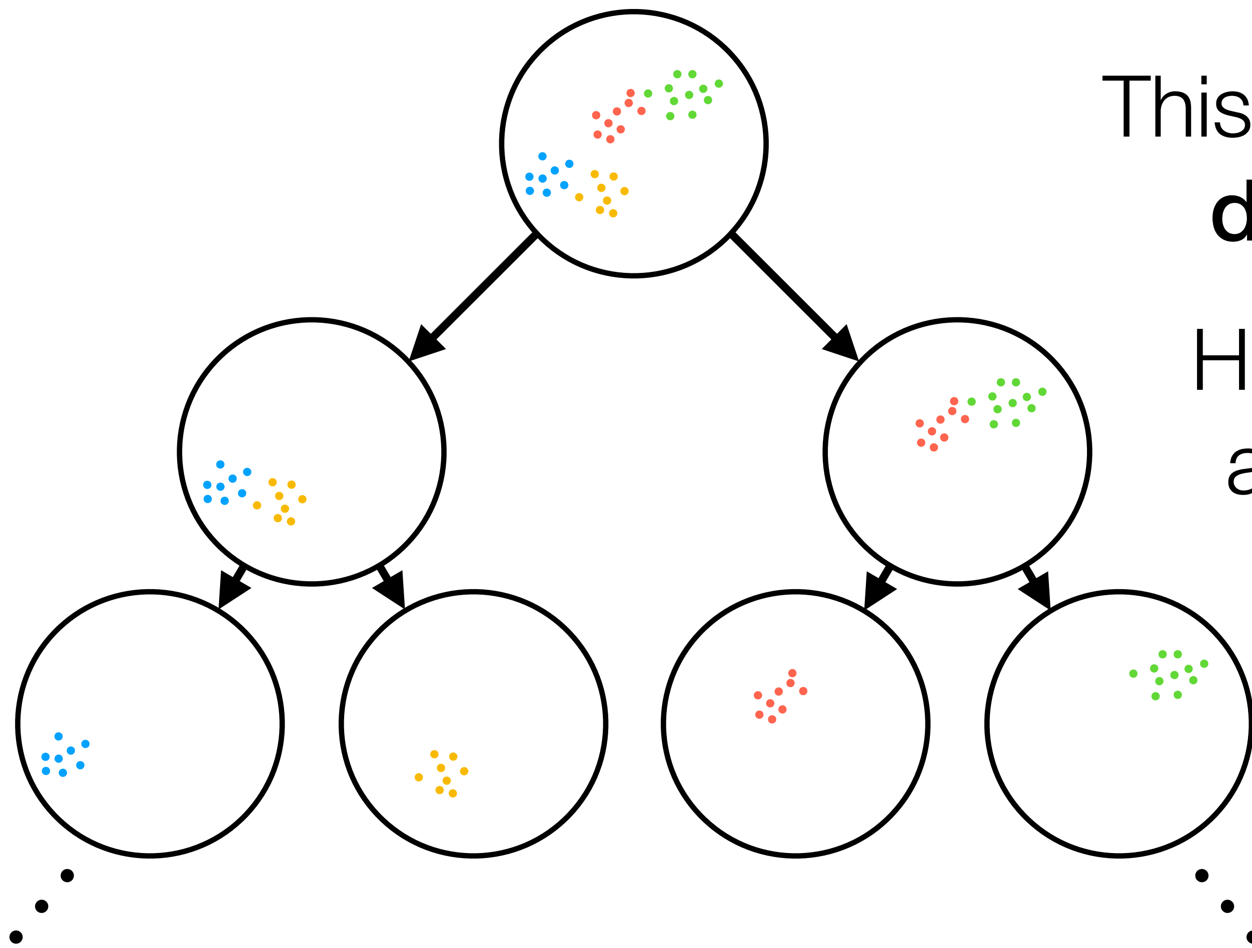

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Divisive clustering uses *global* information and keeps splitting

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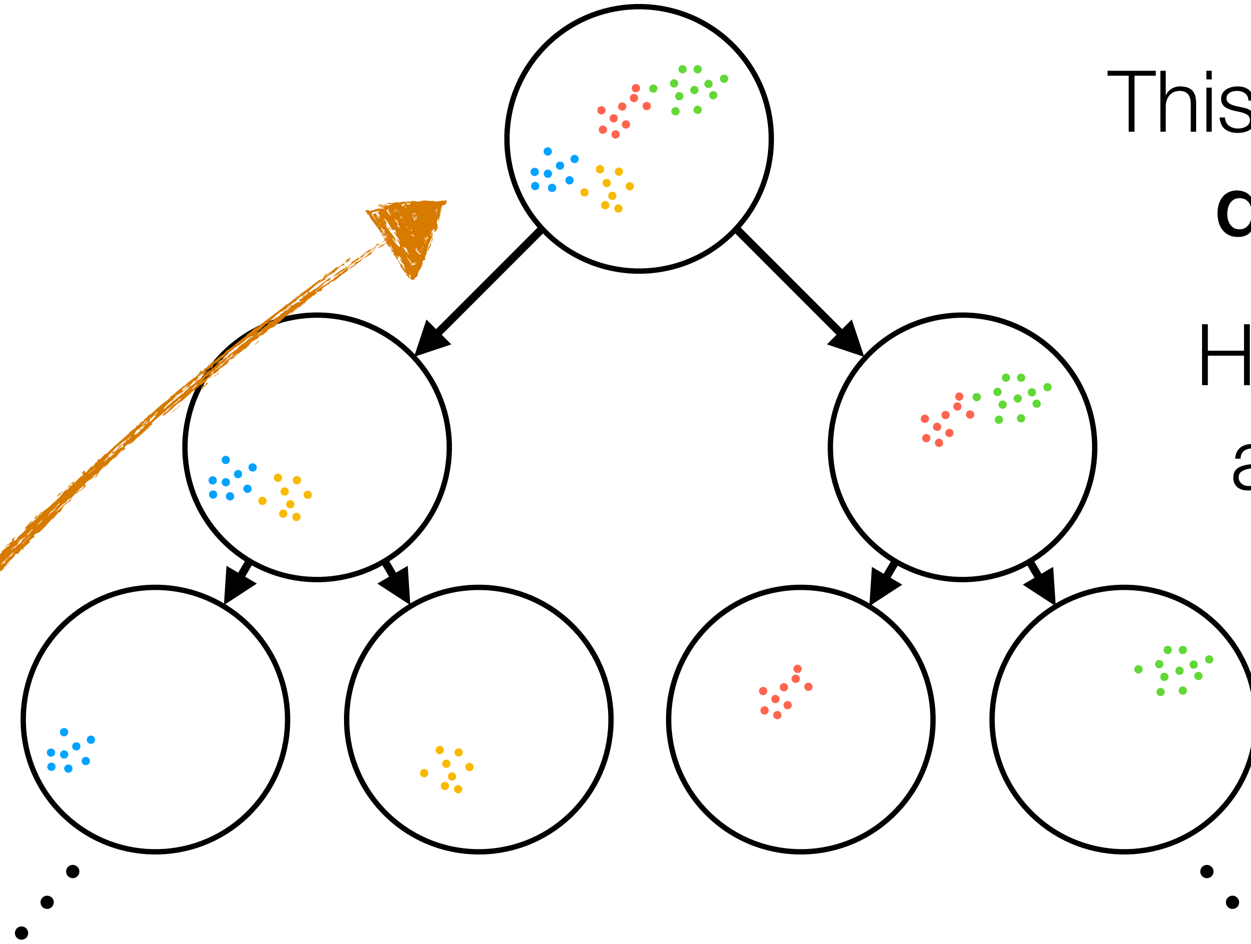

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Agglomerative clustering goes the other way

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Agglomerative Clustering

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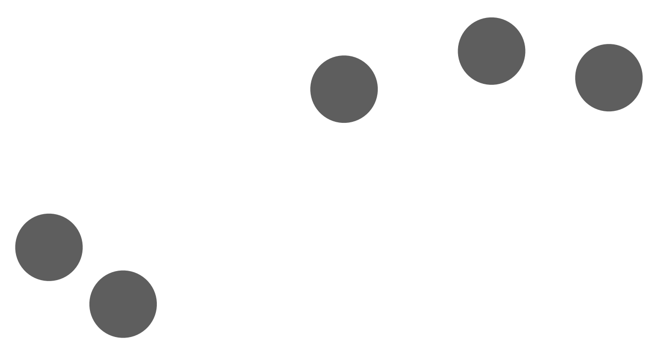

Agglomerative Clustering

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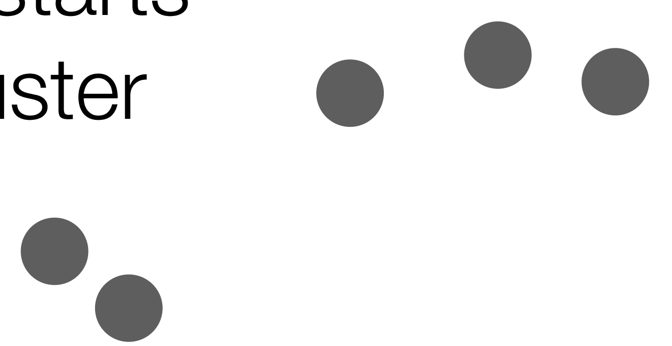

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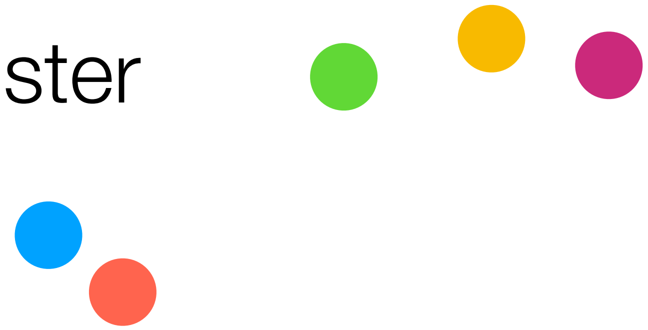

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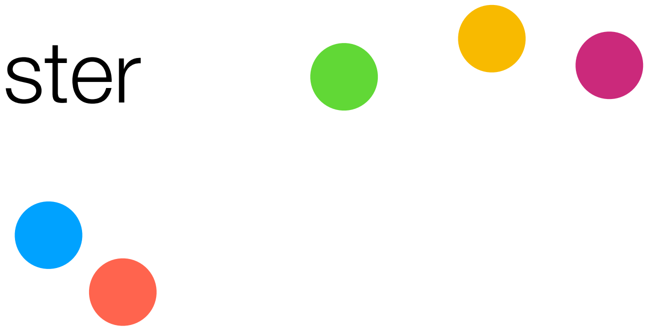

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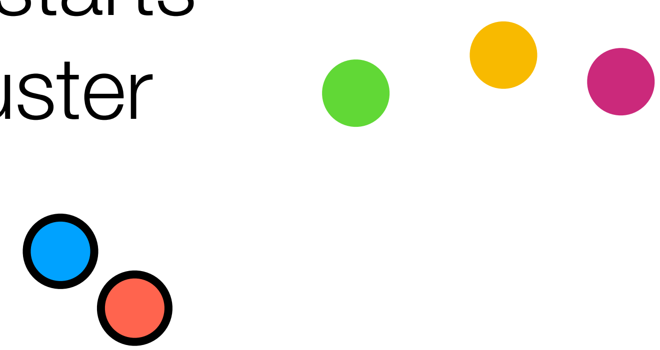

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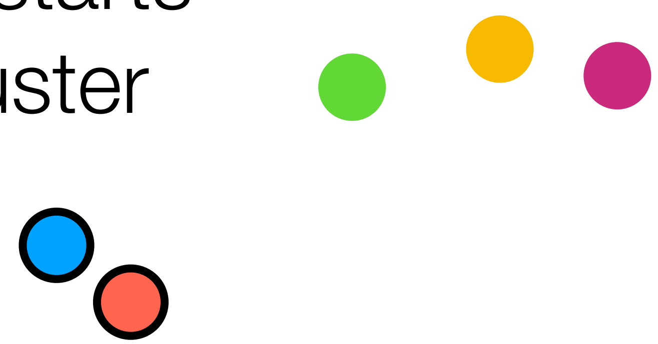

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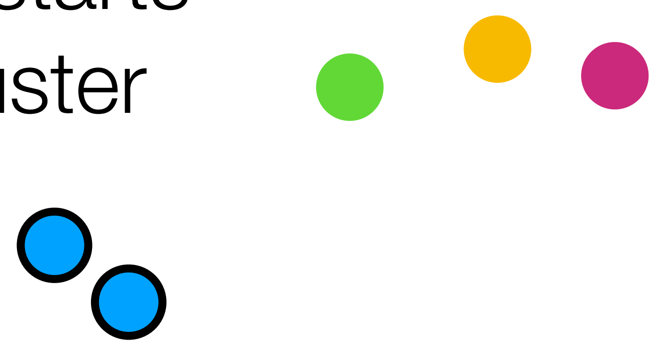

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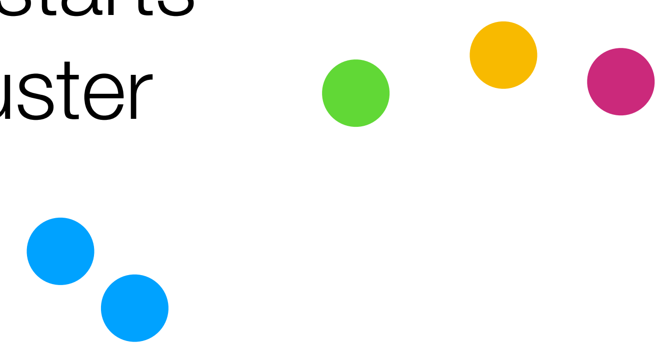

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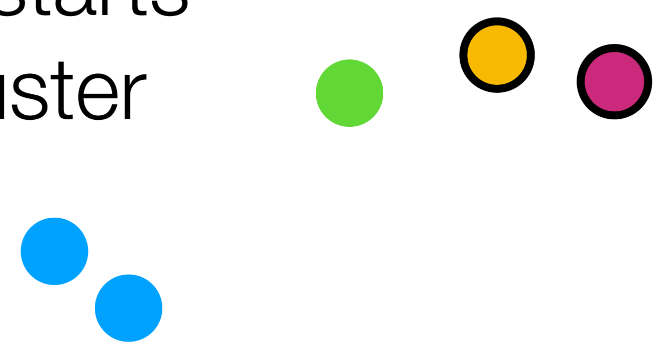

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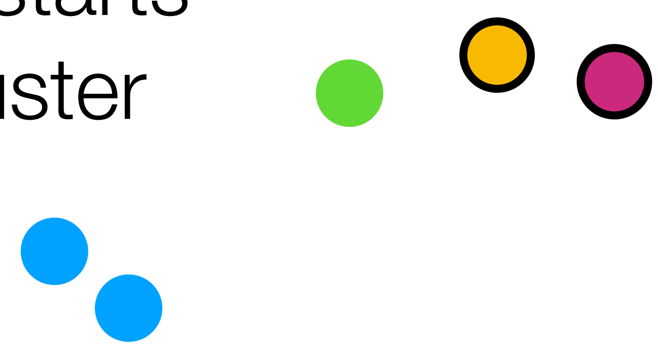

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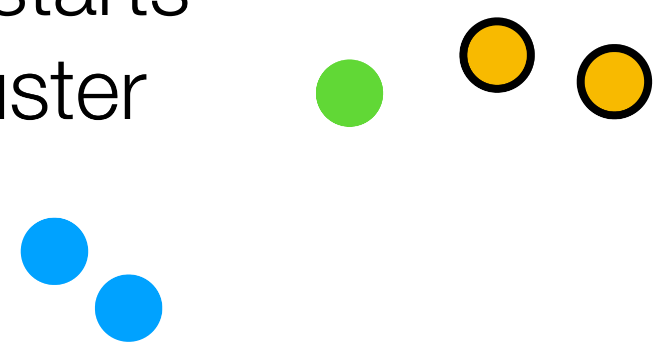

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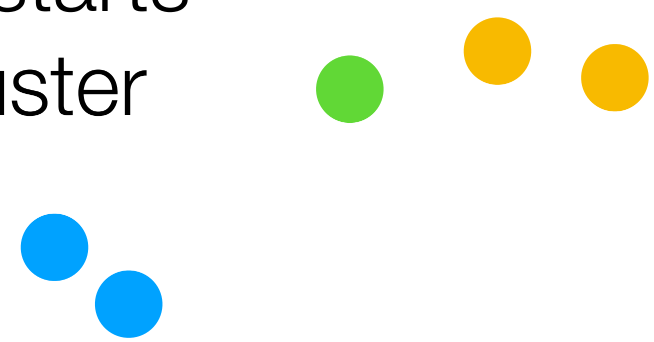

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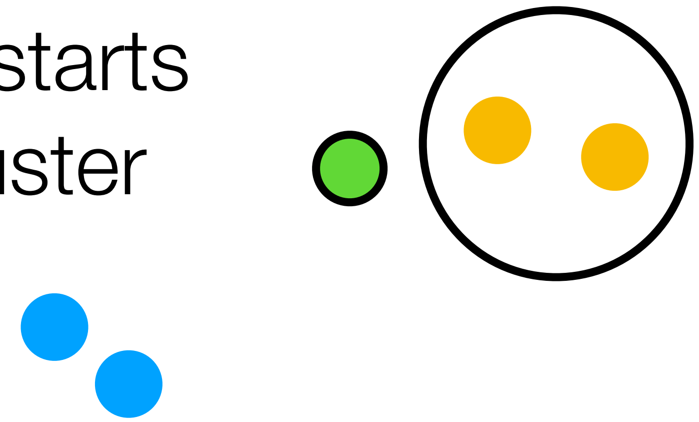

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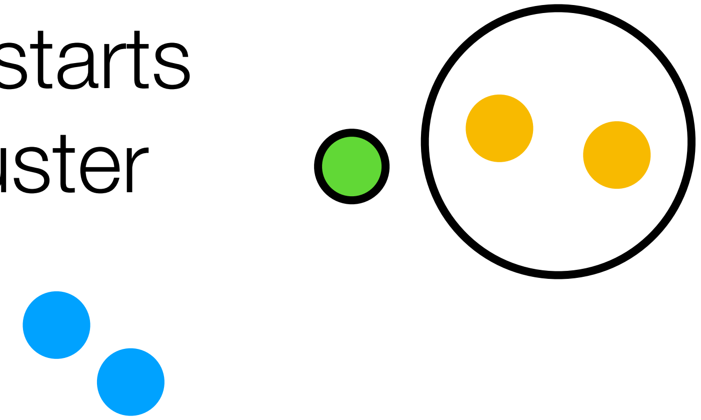

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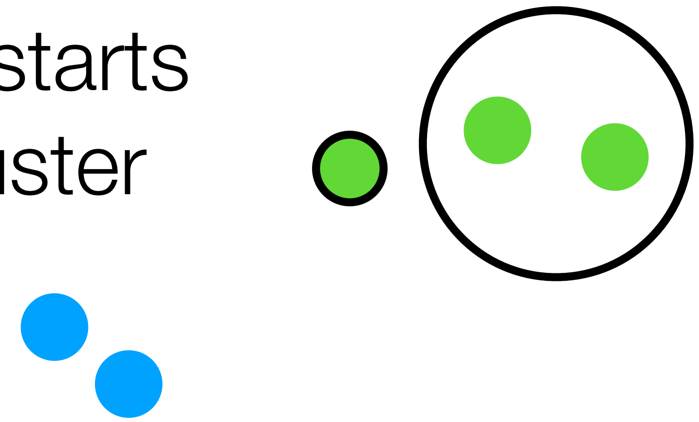

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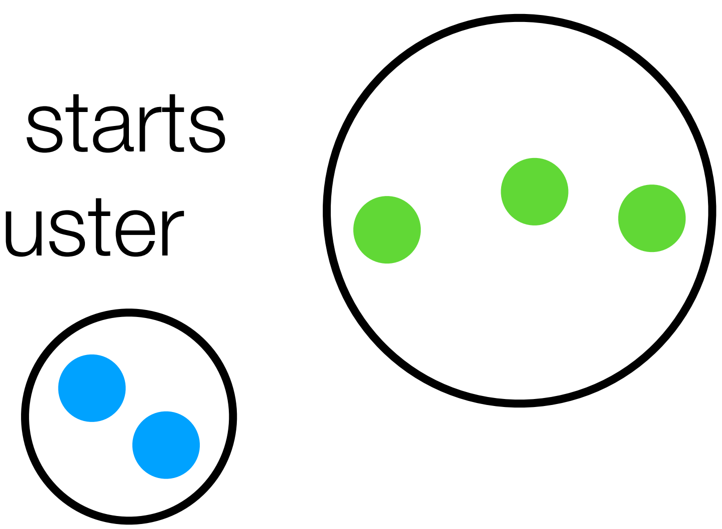

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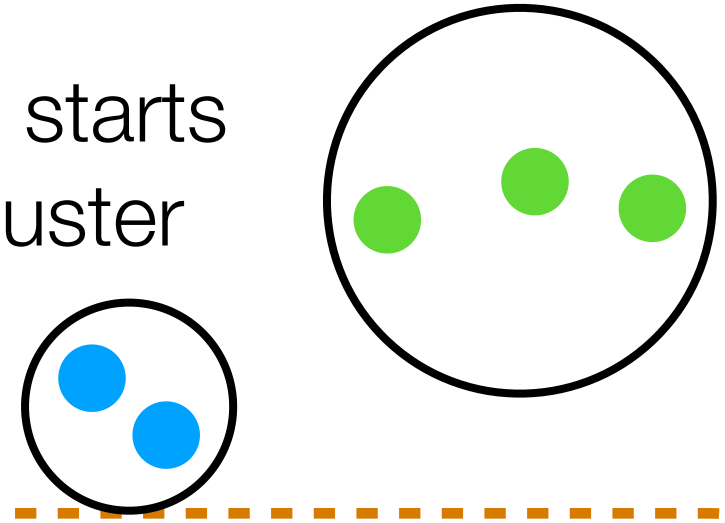

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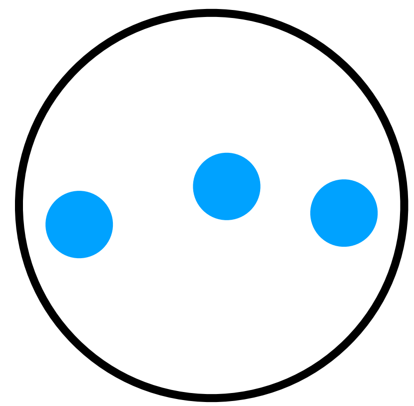

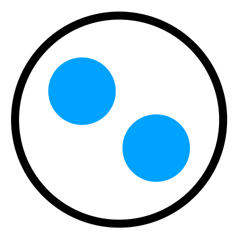

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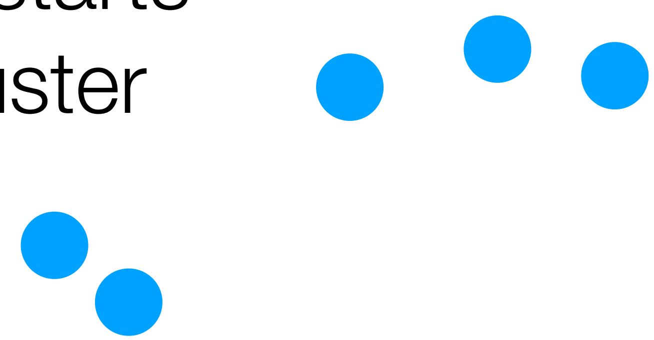

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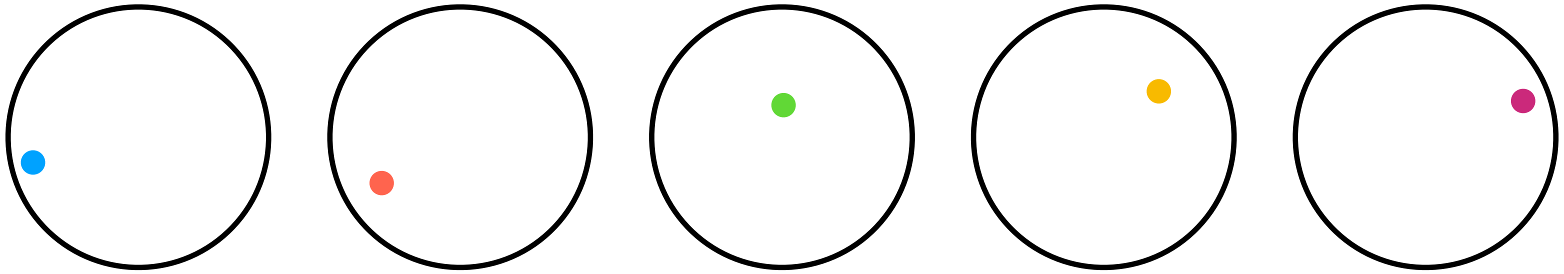
Agglomerative Clustering

Dendrogram

Agglomerative Clustering

Dendrogram



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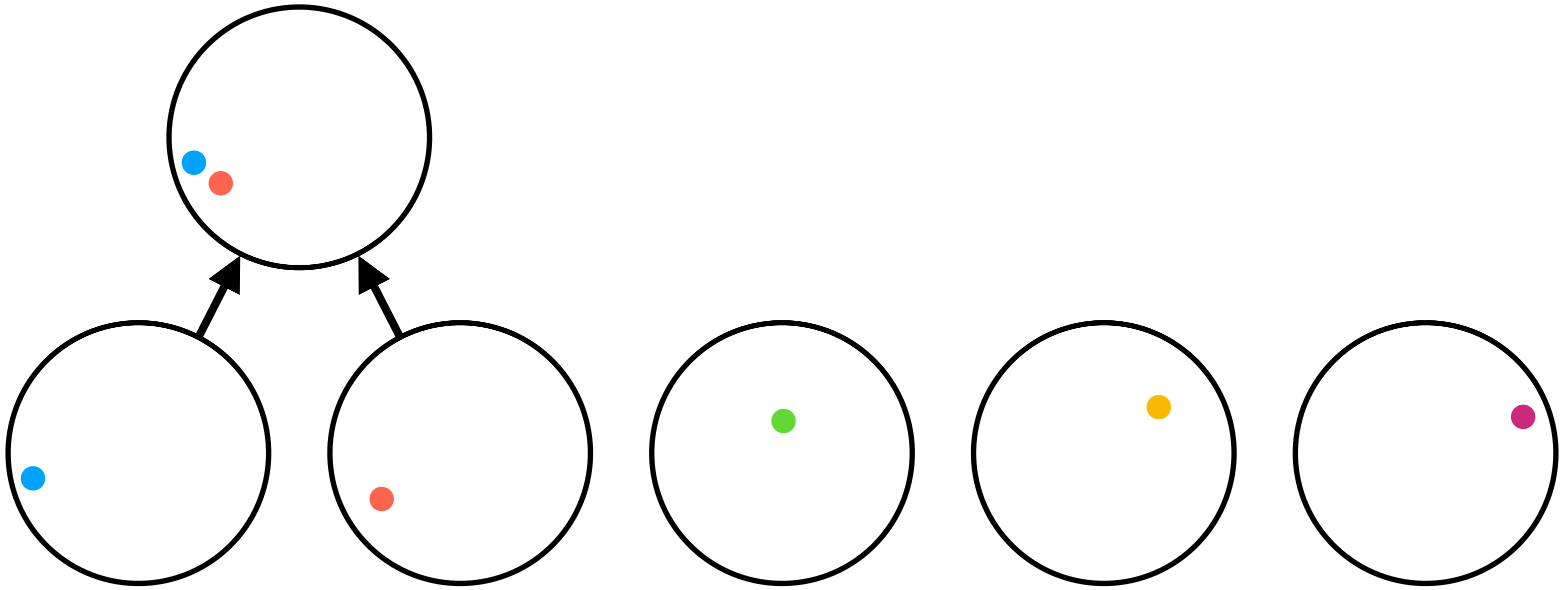

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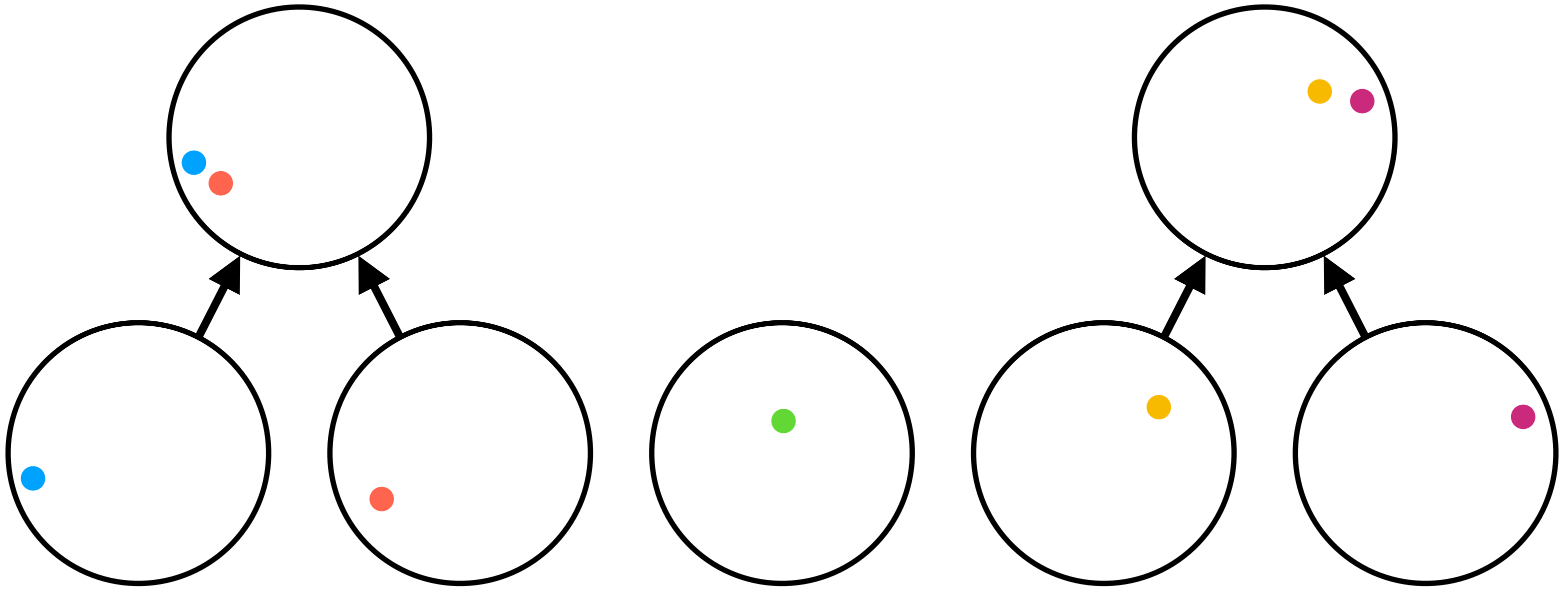

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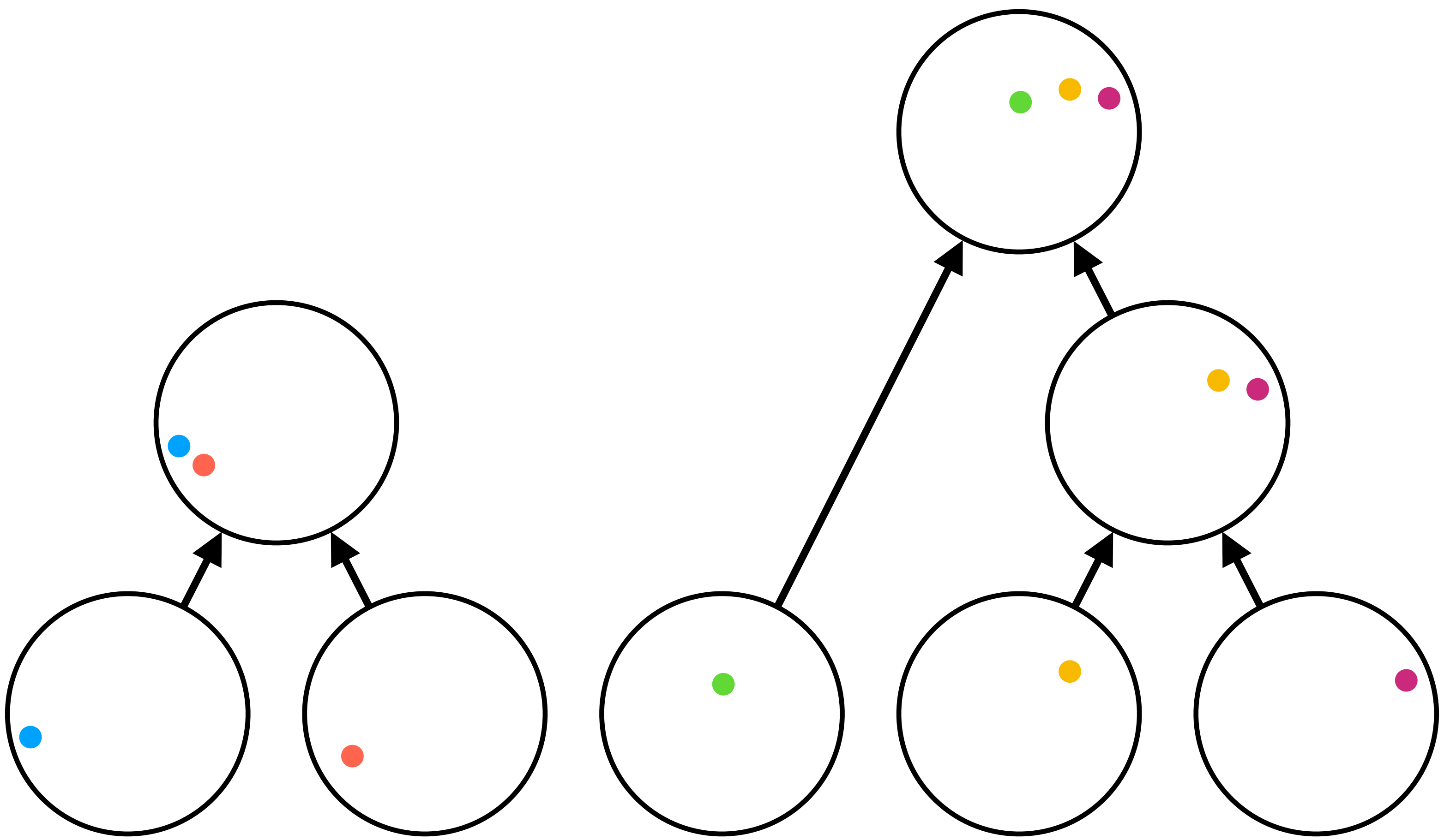

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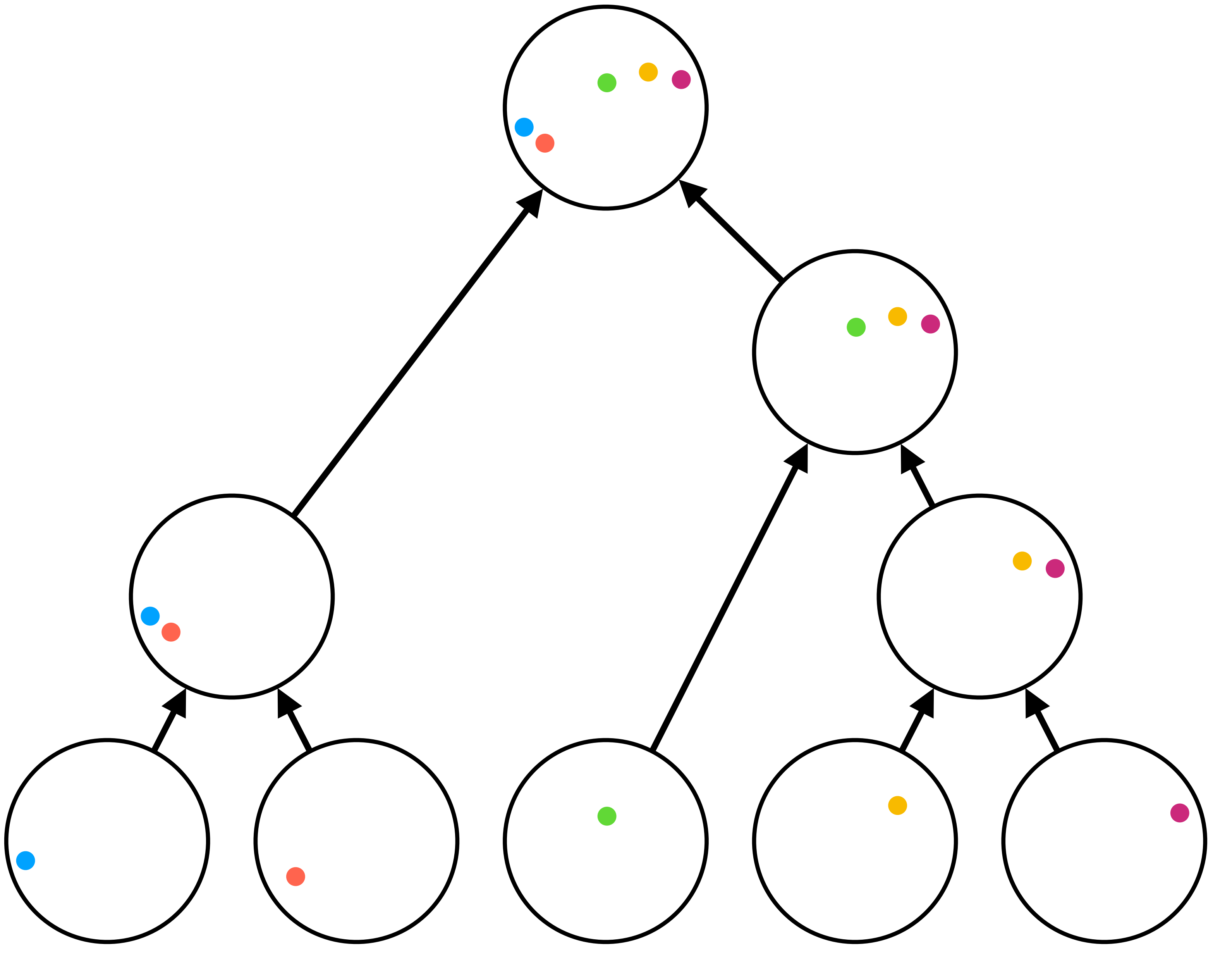

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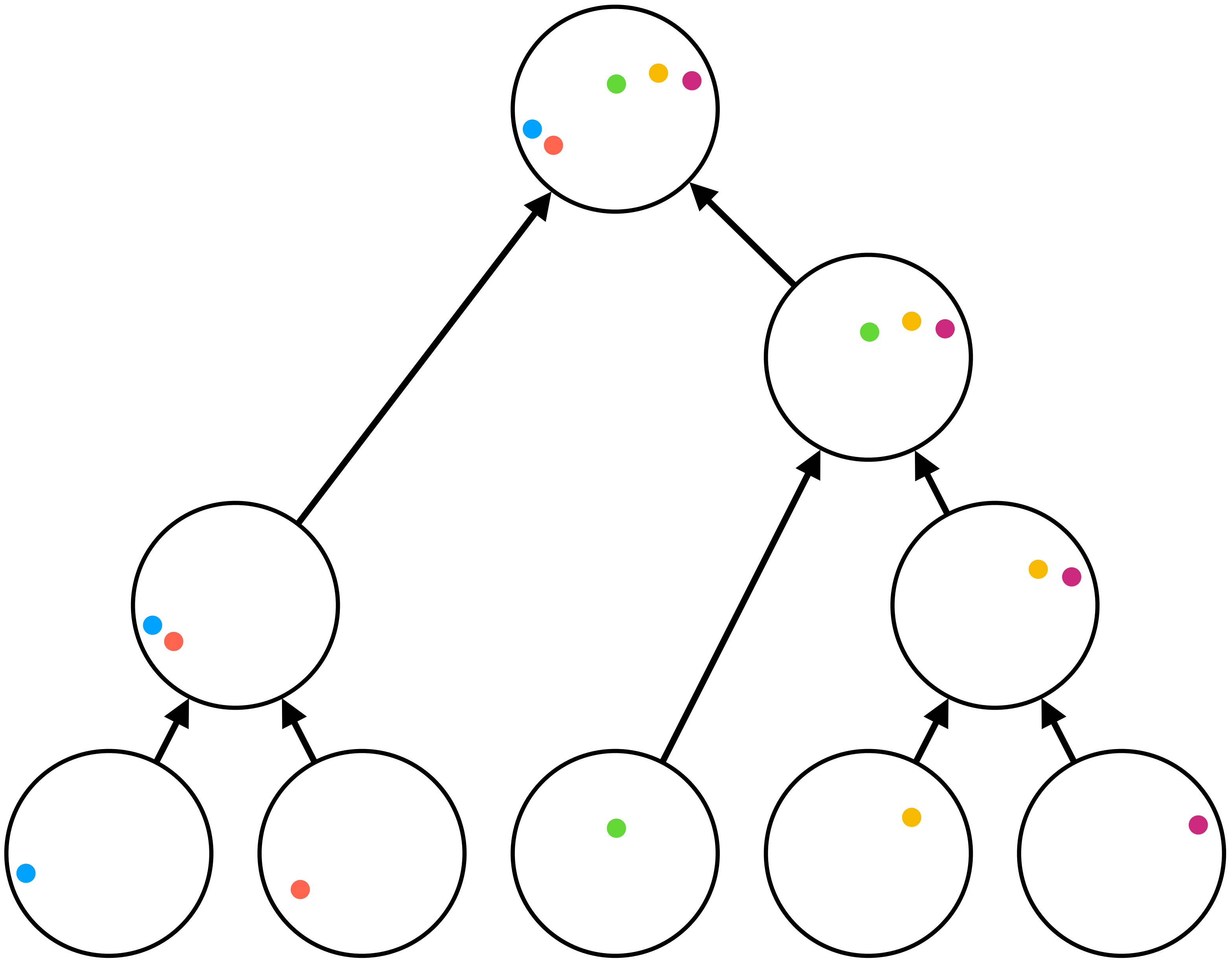

Agglomerative clustering uses *local* information and keeps merging

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Don't have to keep merging until there's 1 cluster!

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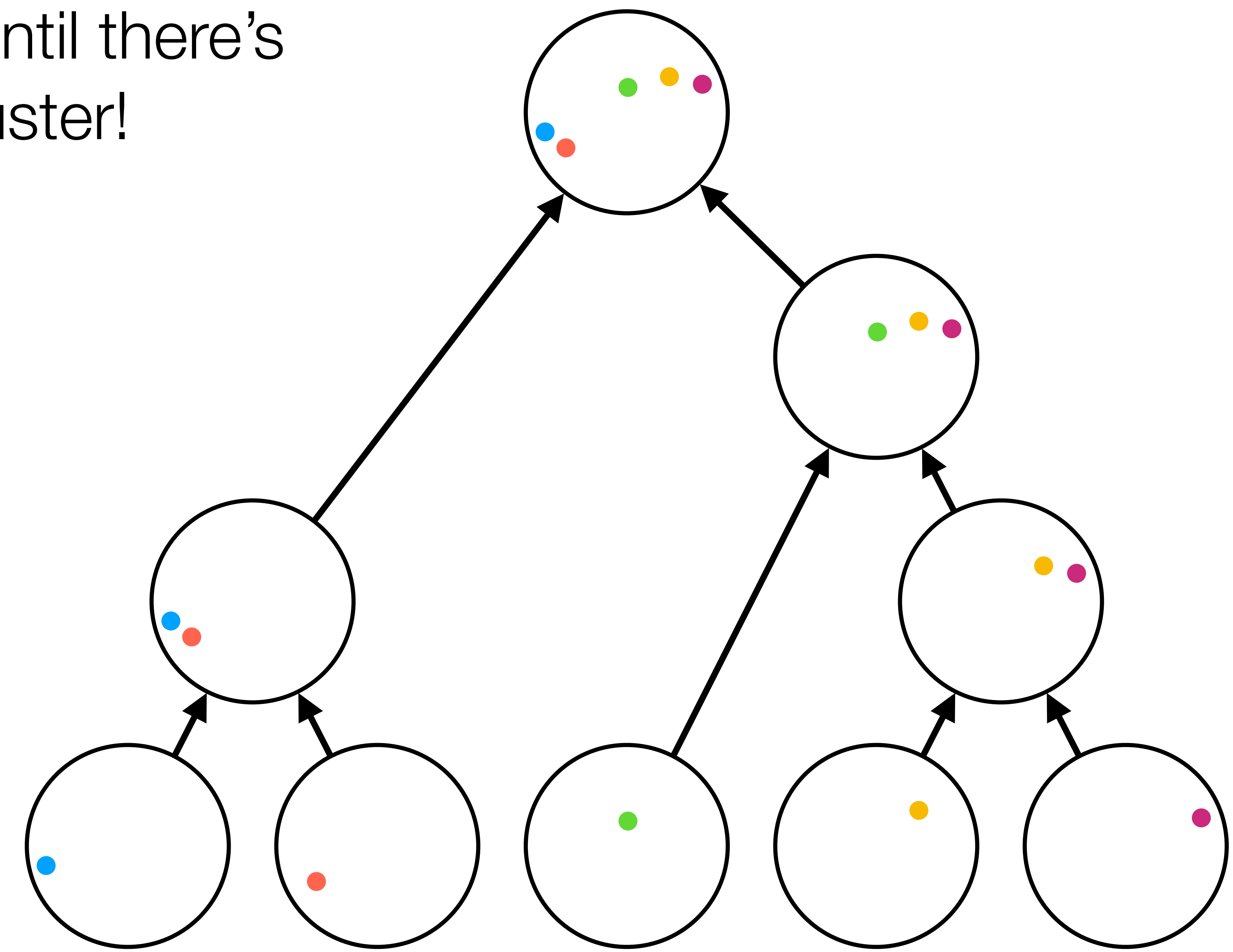

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Don't have to keep merging until there's 1 cluster!

(e.g., stop when closest two clusters have distance between their centers exceed a threshold)

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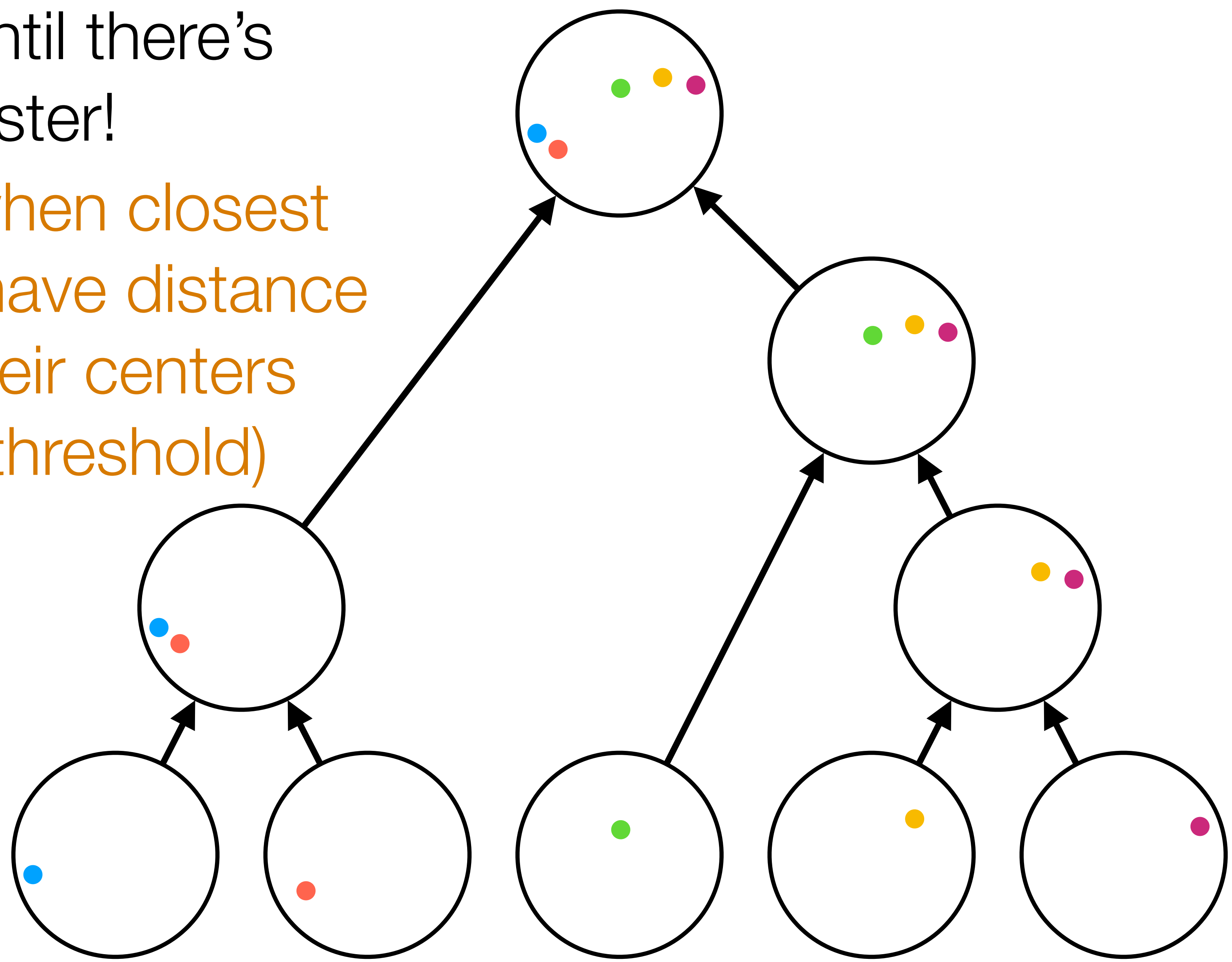

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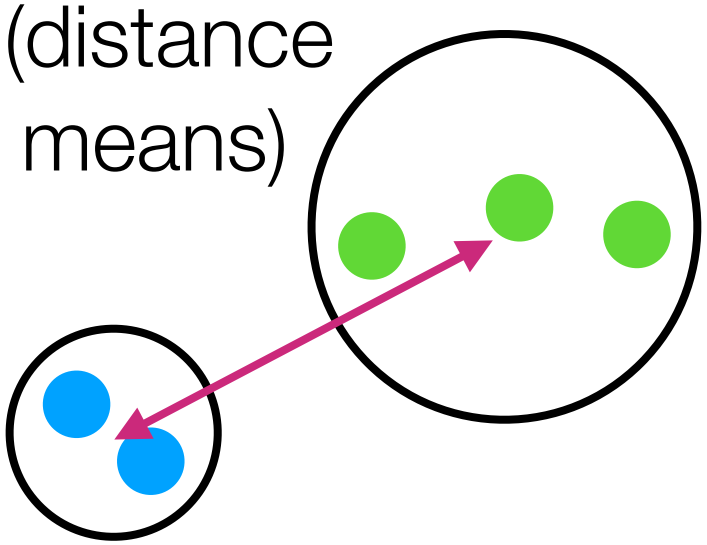

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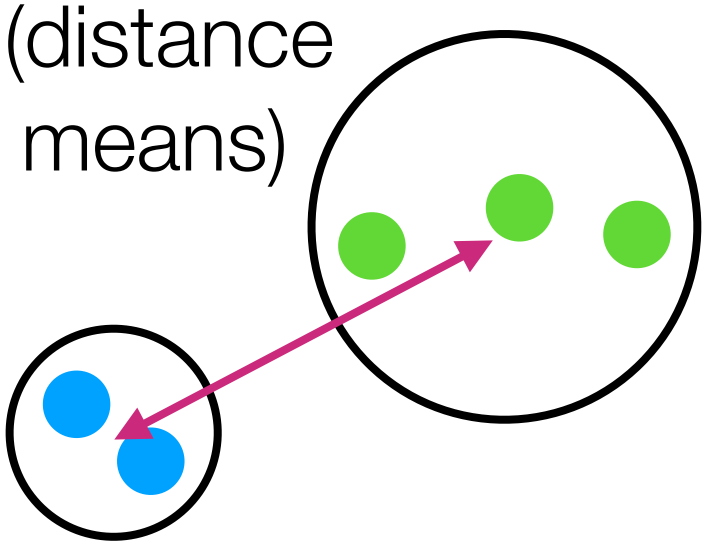

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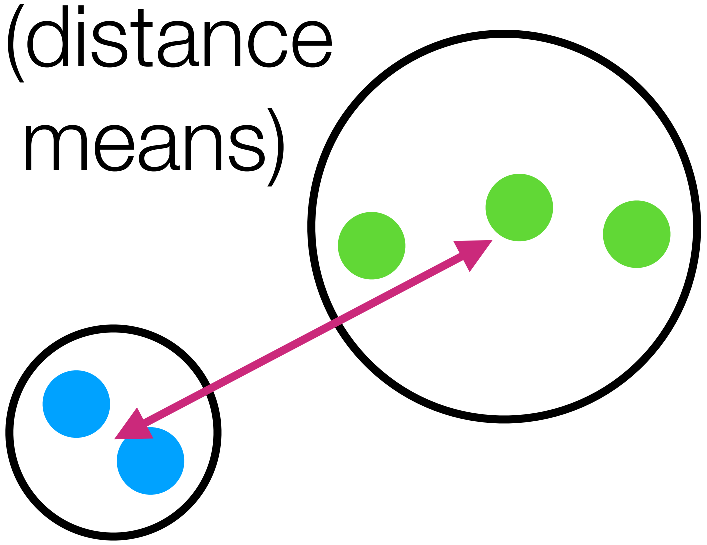

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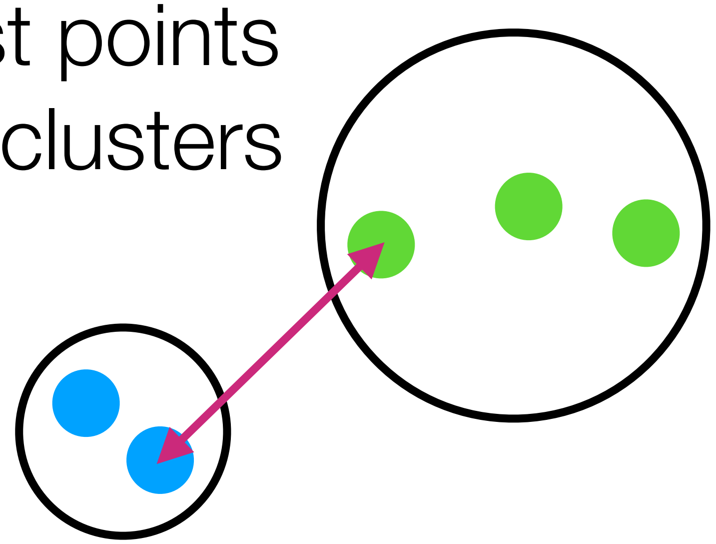

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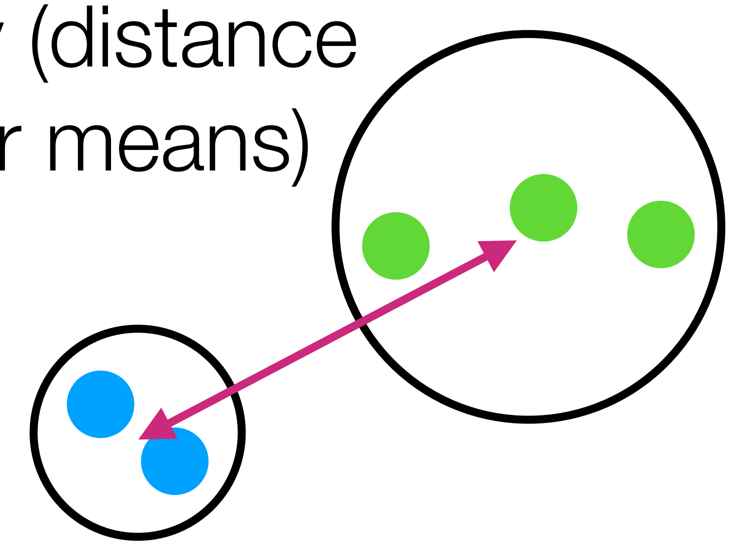

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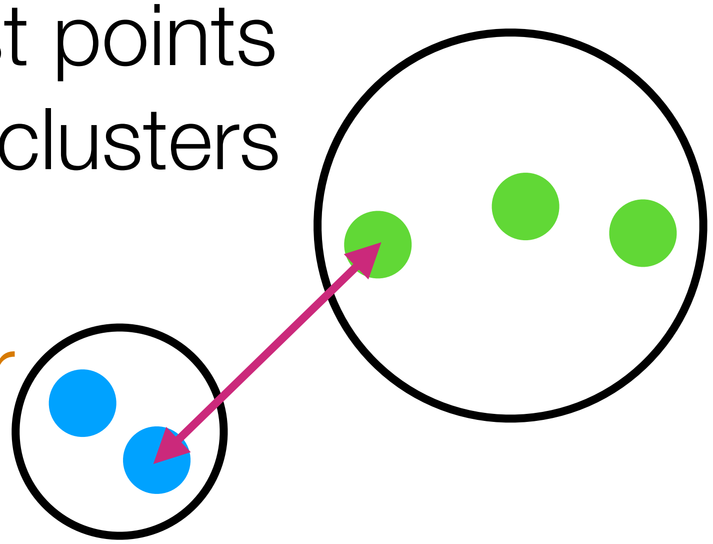

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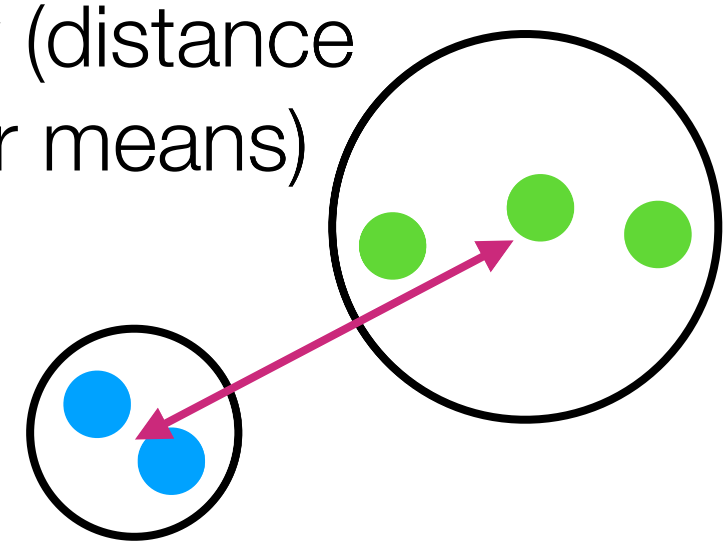

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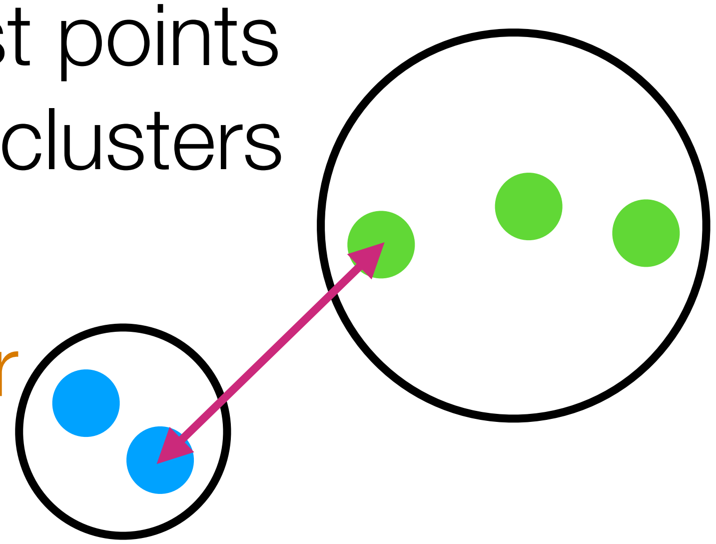

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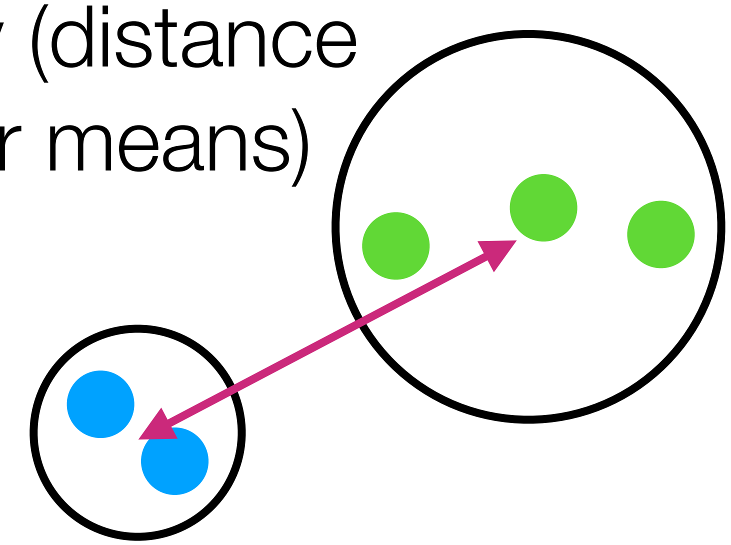

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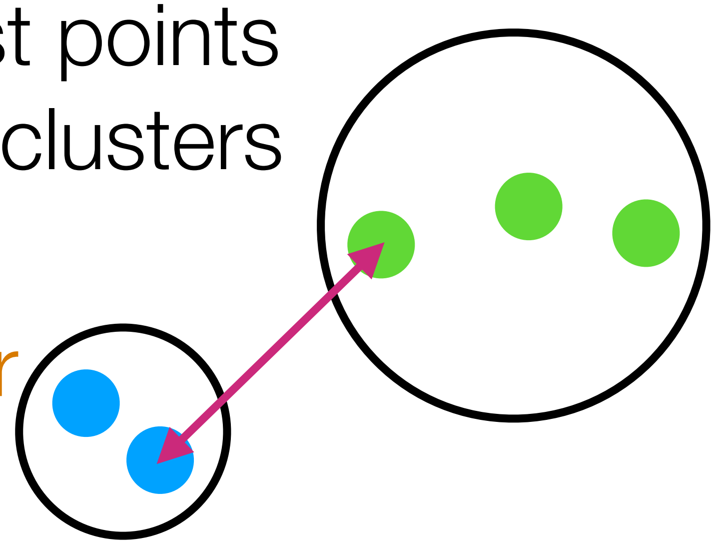

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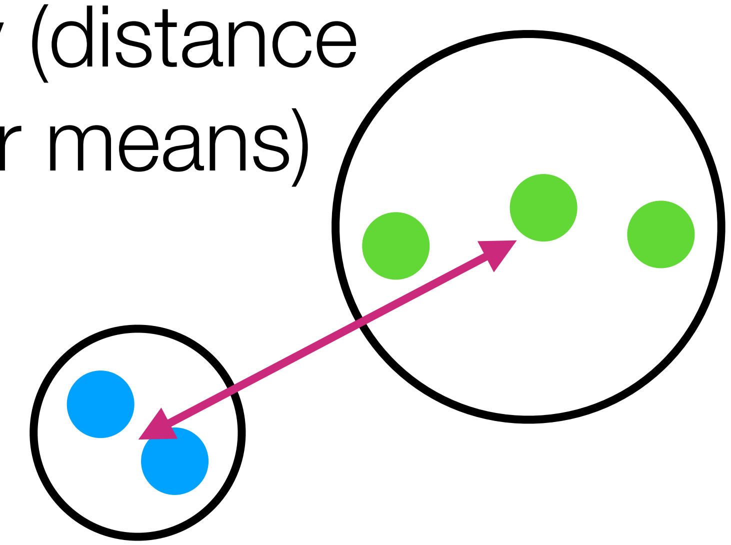

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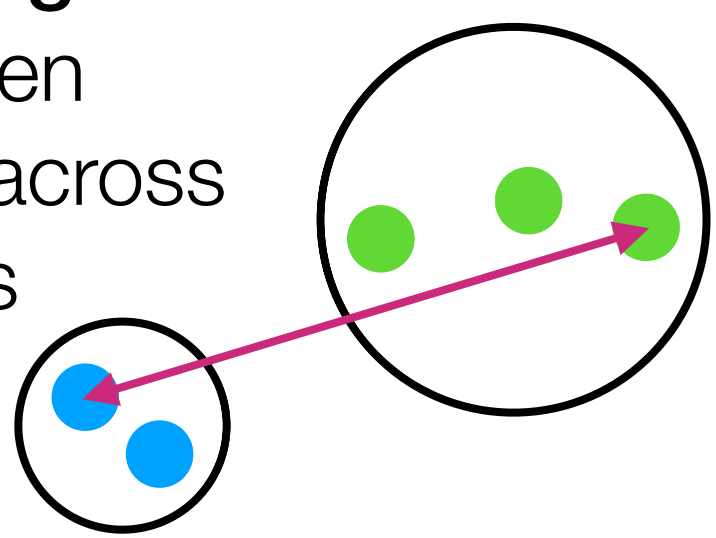

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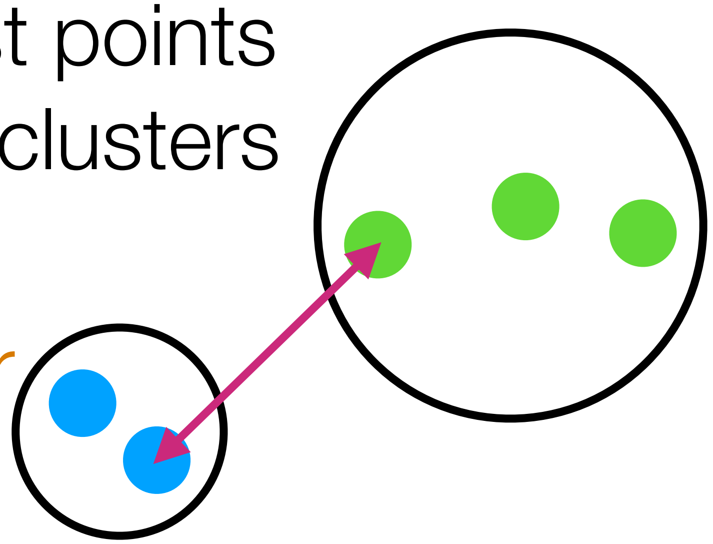

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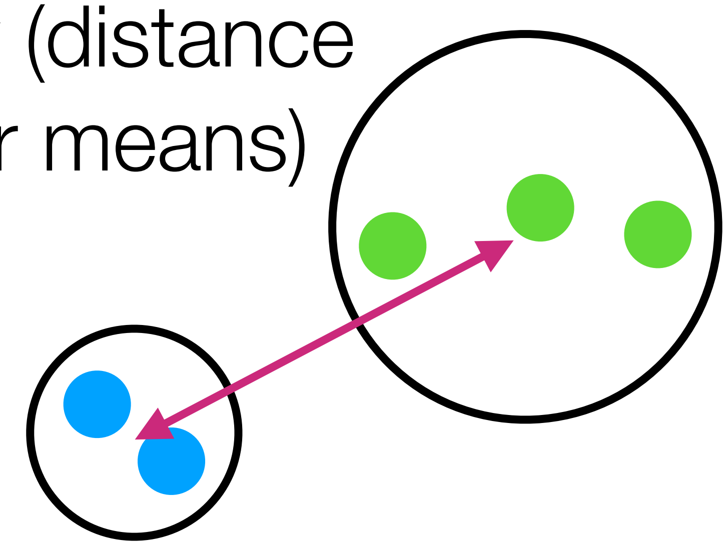

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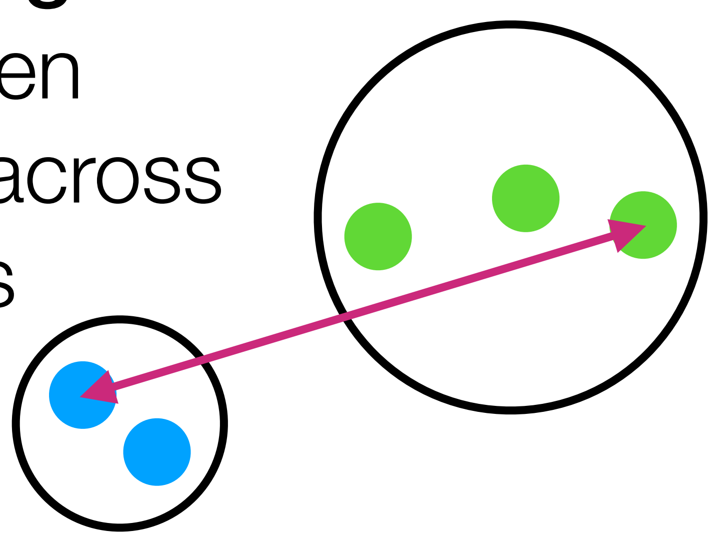

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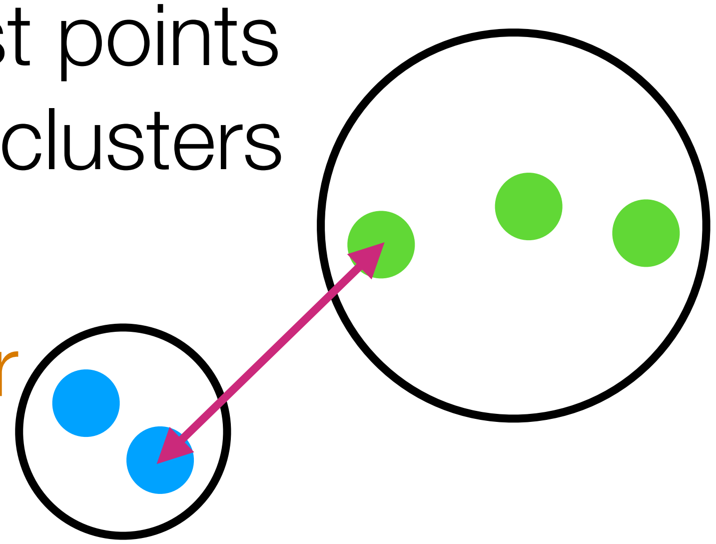

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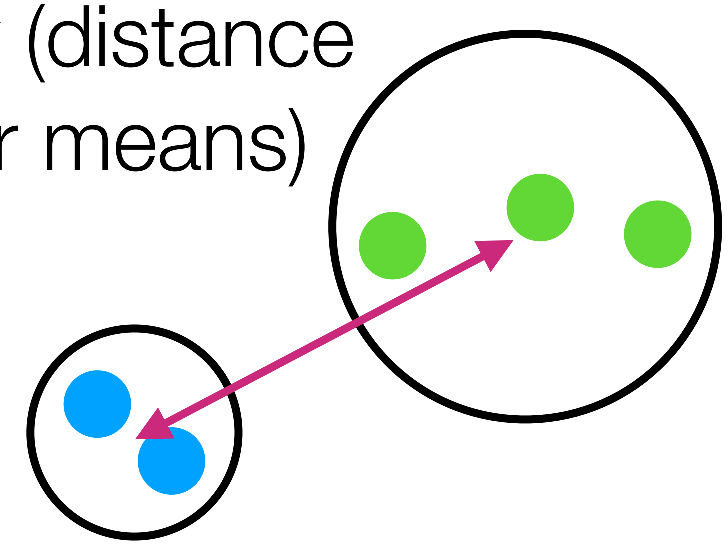

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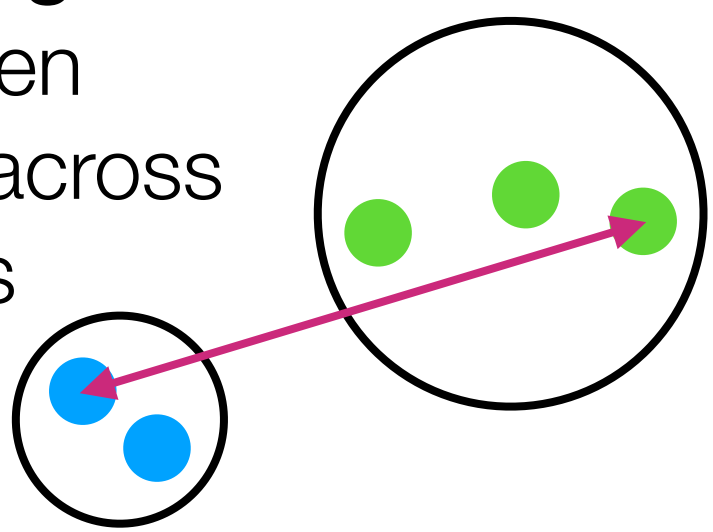

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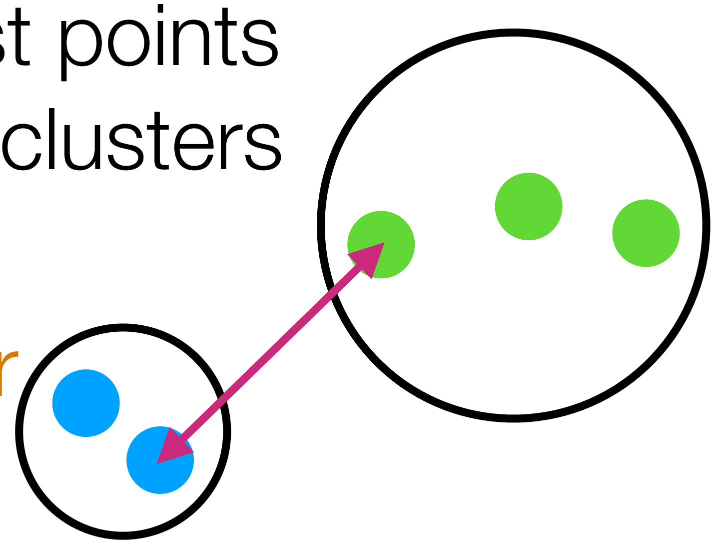

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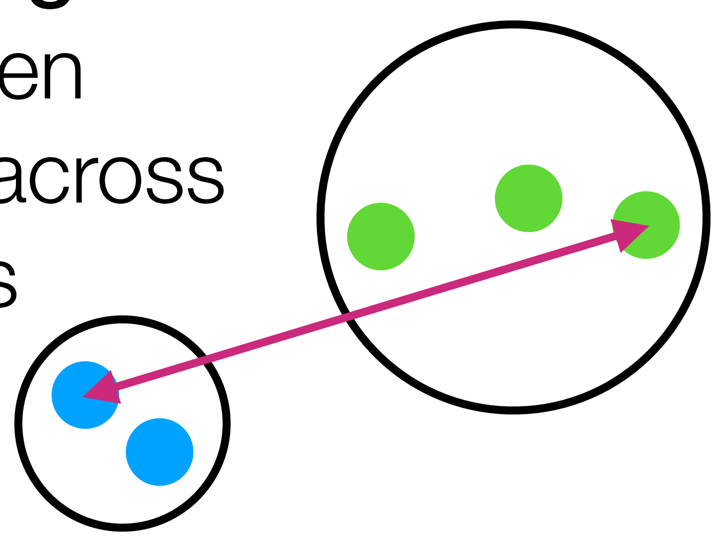

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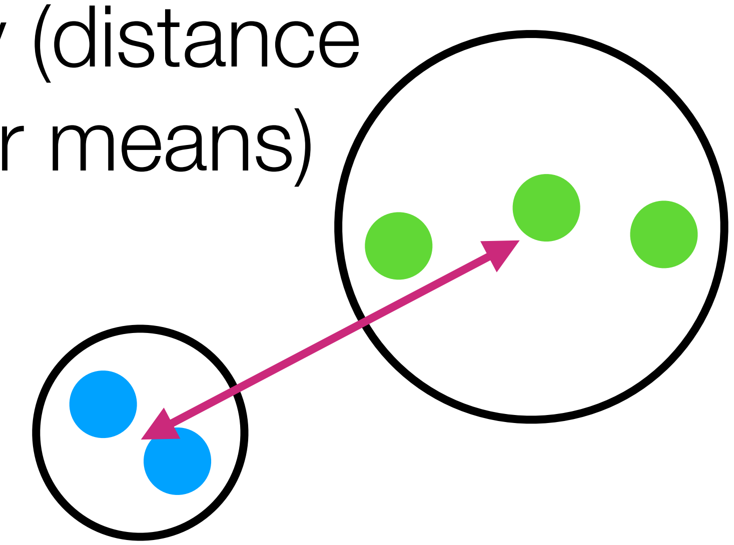

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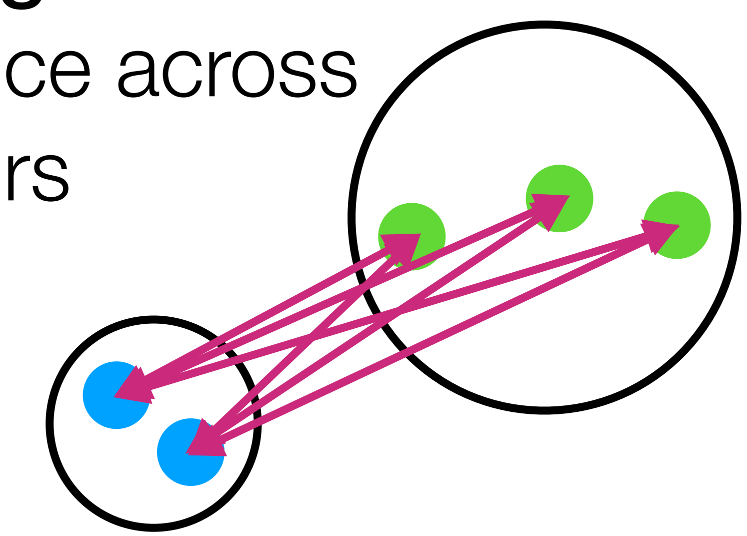

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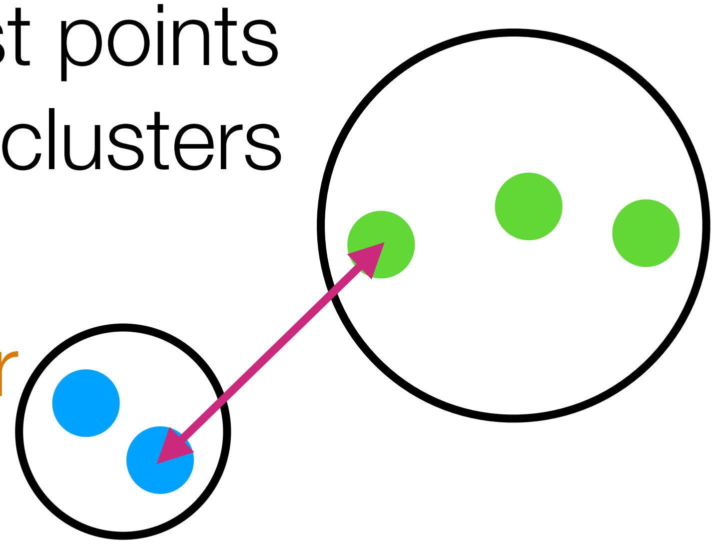

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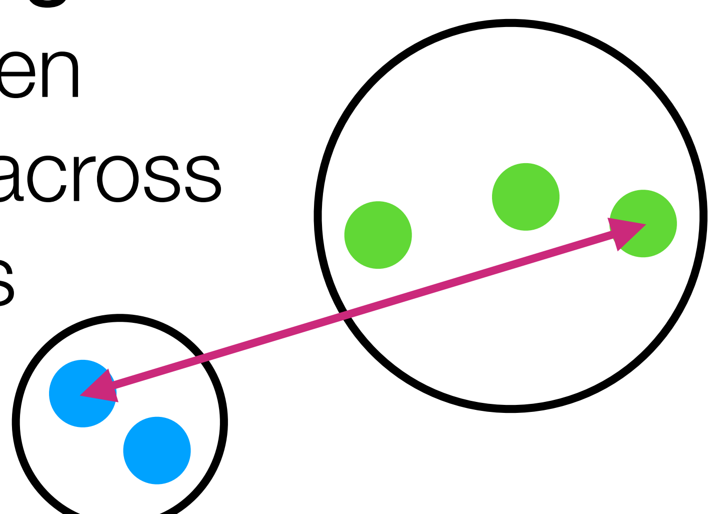

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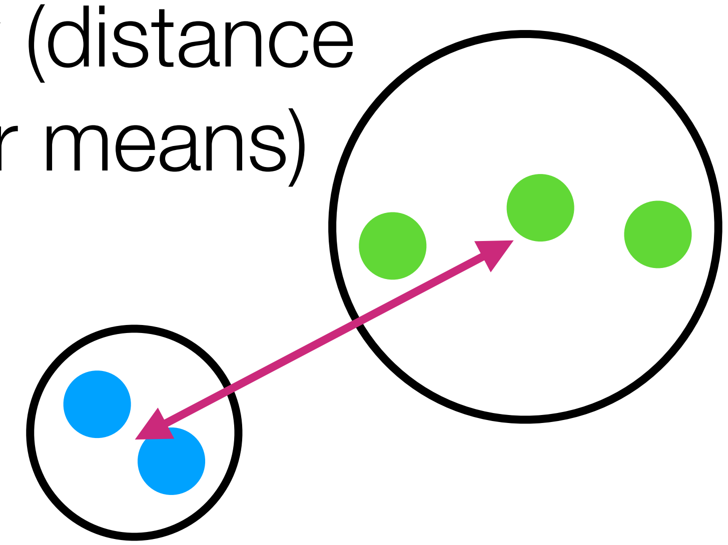

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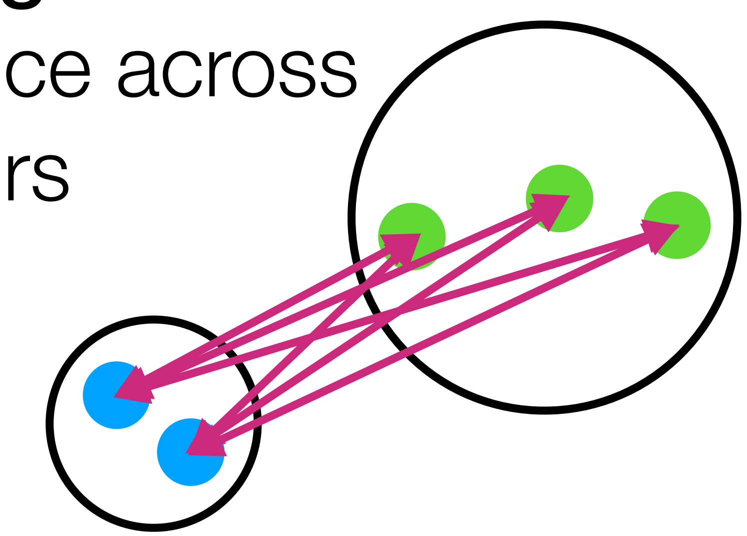

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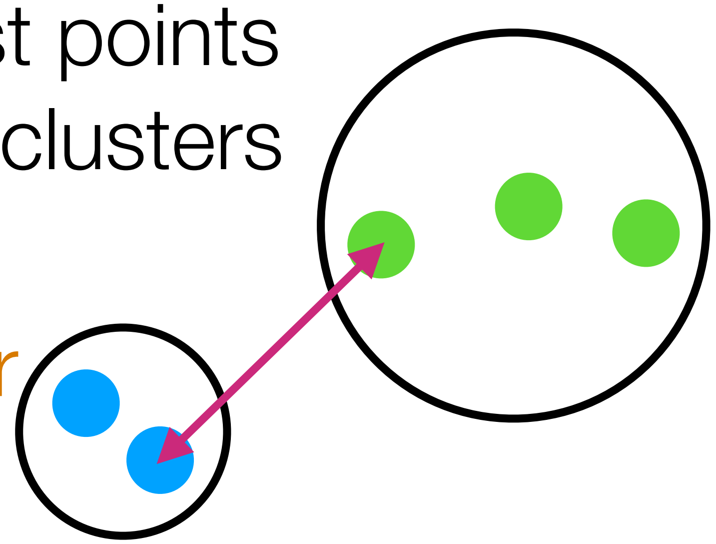

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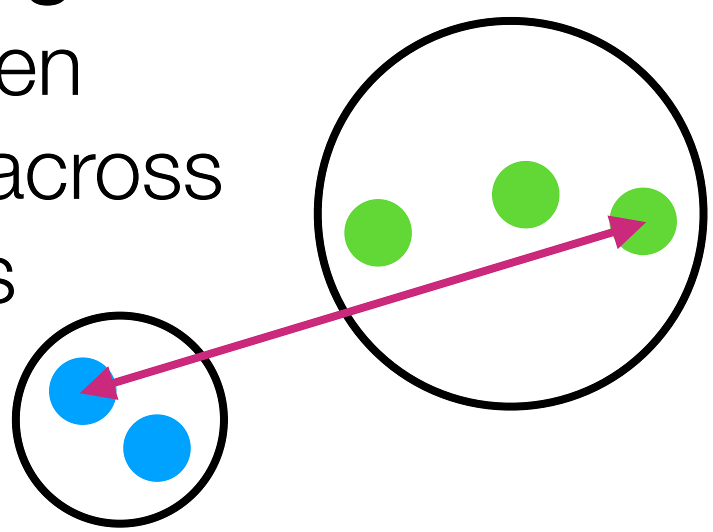

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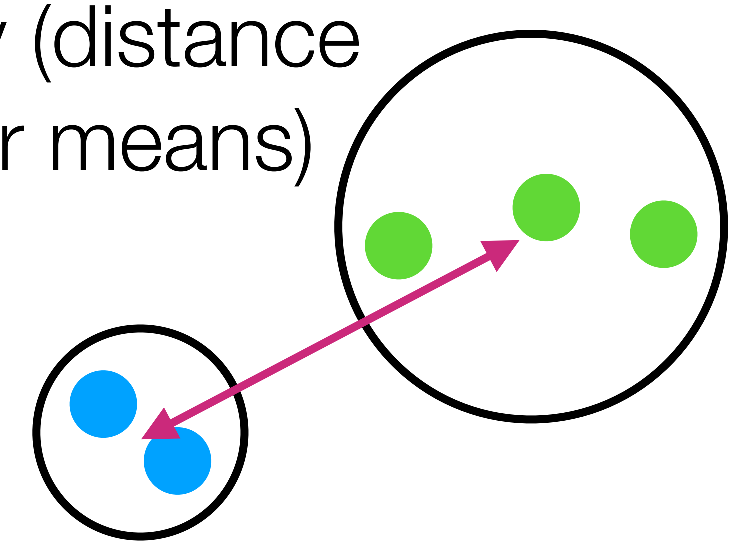

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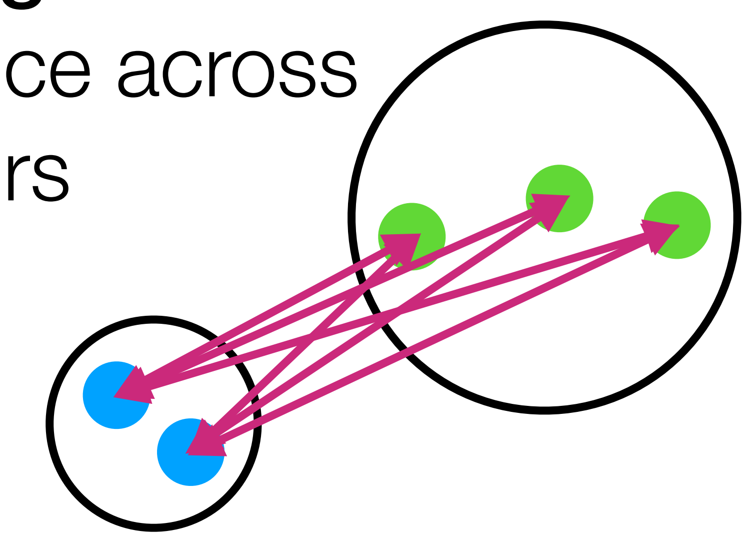

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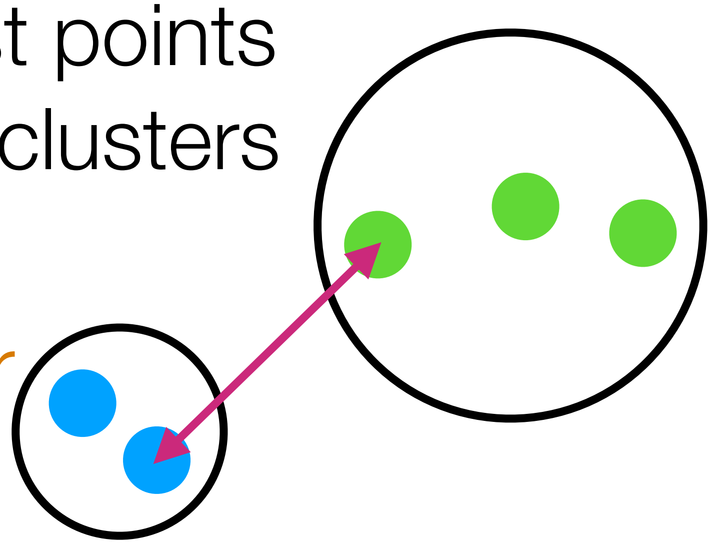

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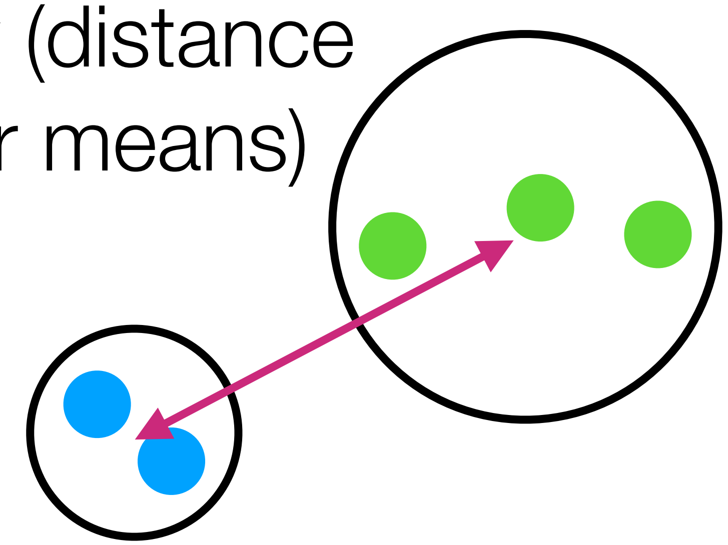

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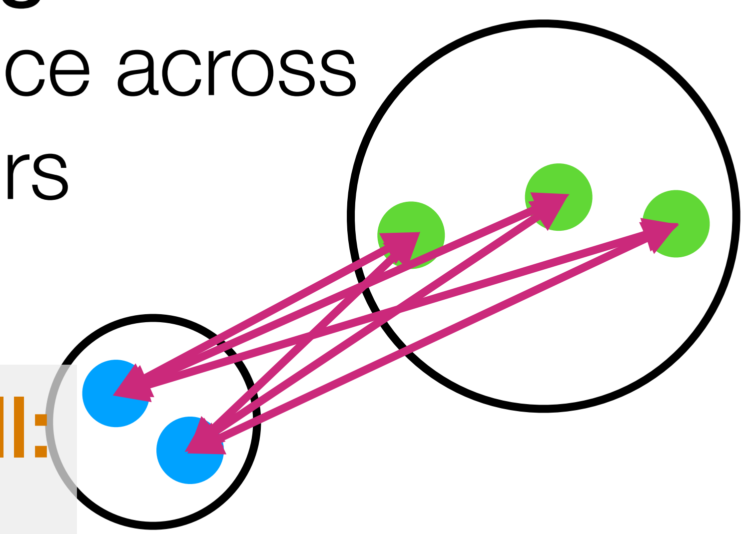

There are other ways as well: none are perfect

Going from Similarities to Clusters

There's a whole zoo of clustering methods

Two main categories we'll talk about:

Generative models

1. Pretend data generated by specific model with parameters

2. Learn the parameters ("fit model to data")

3. Use fitted model to determine cluster assignments

Hierarchical clustering

Top-down: Start with everything in 1 cluster and decide on how to recursively split

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Different split/merge criteria lead to clusters that look specific ways (e.g., chaining, crowding)

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(using opioid death rate data across 37 years)

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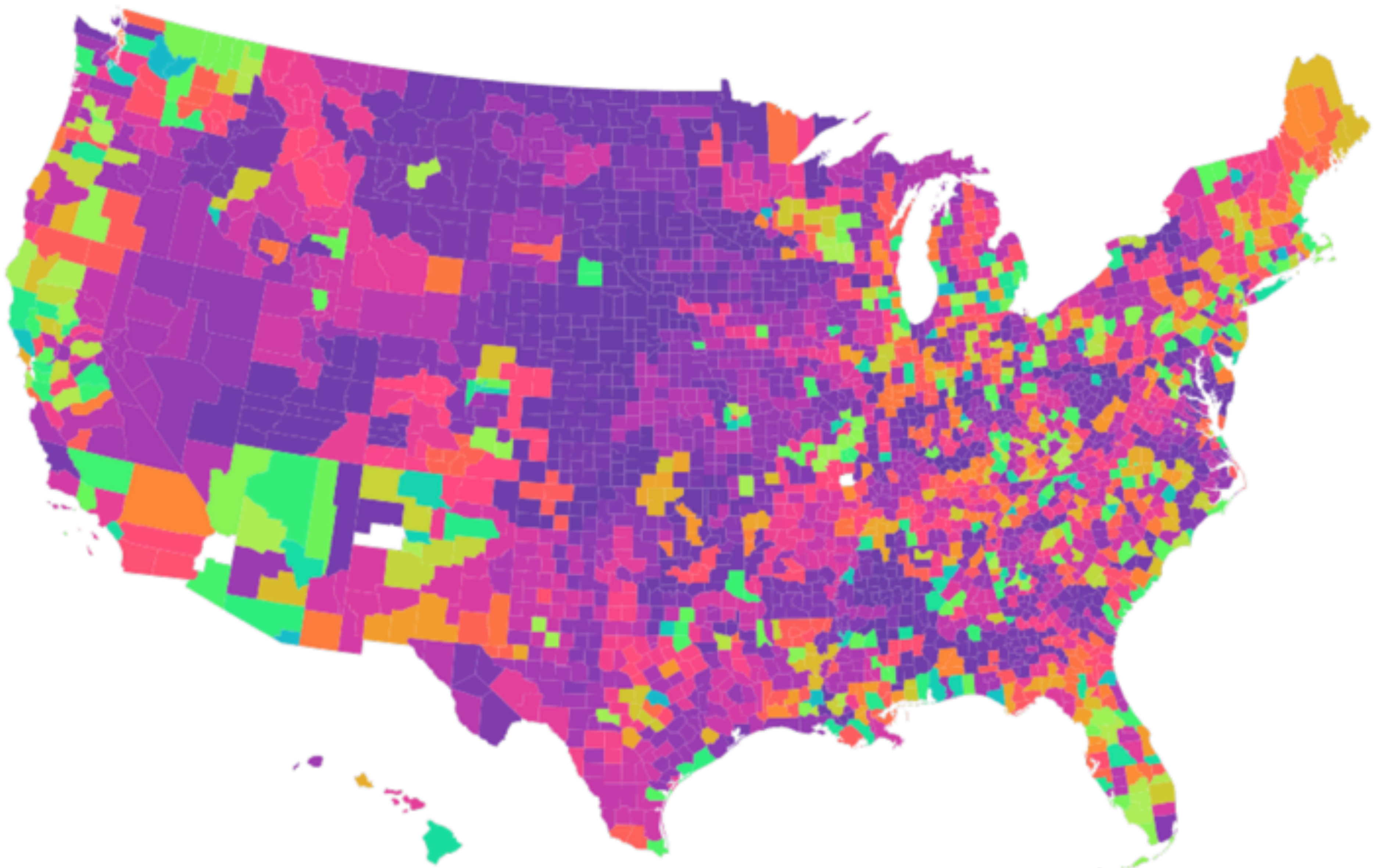

Image source: Amanda Coston

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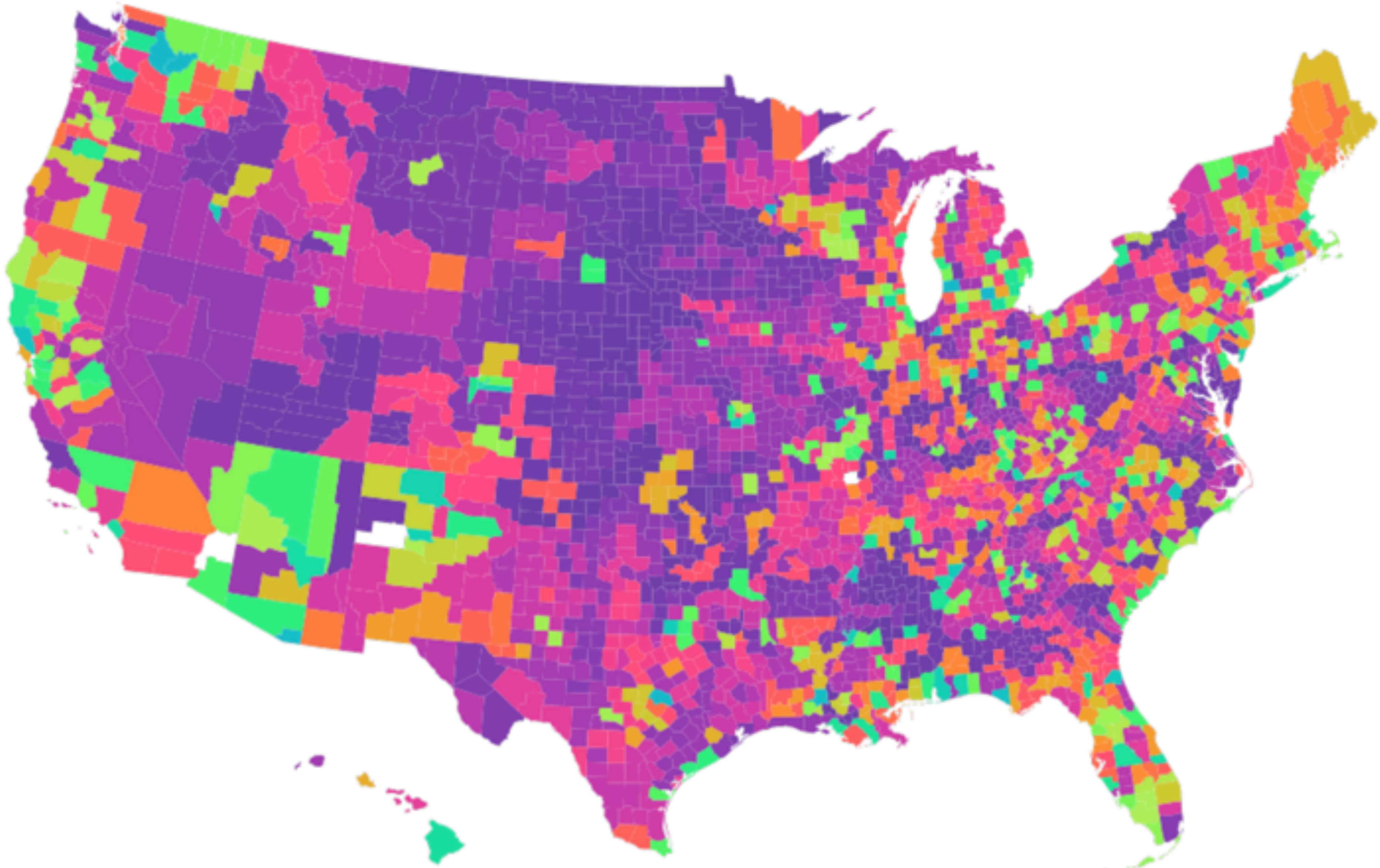

No need to predict which cluster new counties should belong to, since we're already looking at all U.S. counties!

Image source: Amanda Coston

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- Also: remember the recommendation system setup?
  - **Co-clustering** is the problem of clustering both users and items at the same time (`sklearn` has a few methods)

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- What features to even cluster on?
- Does Euclidean distance make sense for your application, or do you use some custom distance function?
- Do you care about figuring out which cluster new points belong to?
- After you run the clustering algorithm, look at what data points ended up in the same cluster and make visualizations (e.g., histogram of various feature values)
  - Do the clusters seem interpretable to you?
  - Compare the cluster centers: do two clusters seem a bit too close and should be merged?

How to Choose a Clustering Method?

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- Can you come up with some heuristic score function to say how good a cluster assignment is?

Clustering

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Later in the course: If you can set up a prediction task, then you can use the prediction task to help guide the clustering

Is Clustering Structure Enough?

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Items

1 2 3 4 5 • • • m

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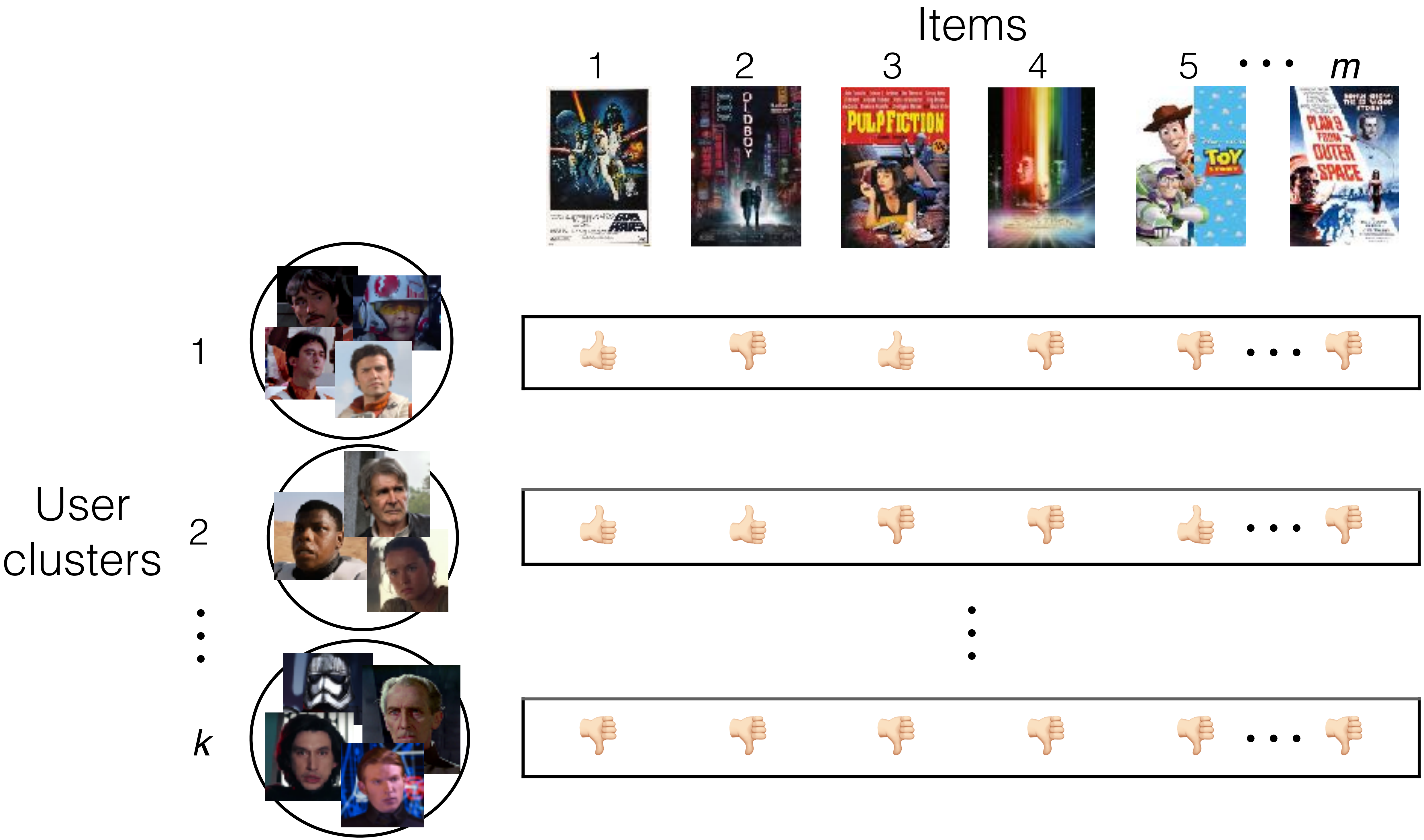

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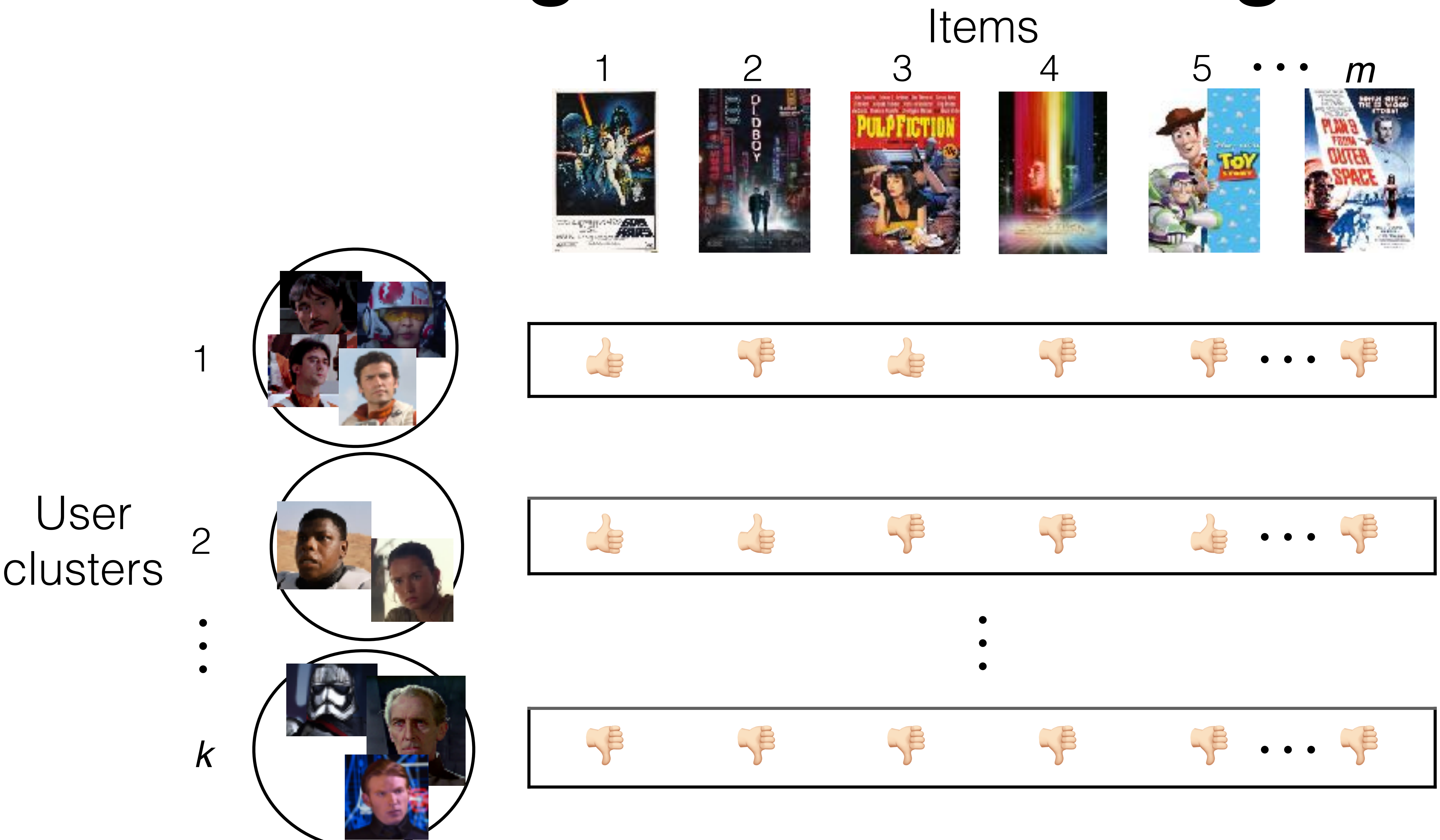

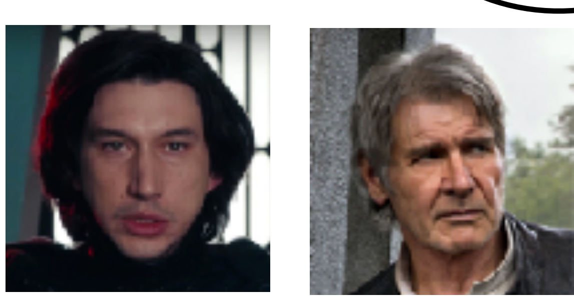

What if these two users shared a Netflix account
(and used the same user profile)?

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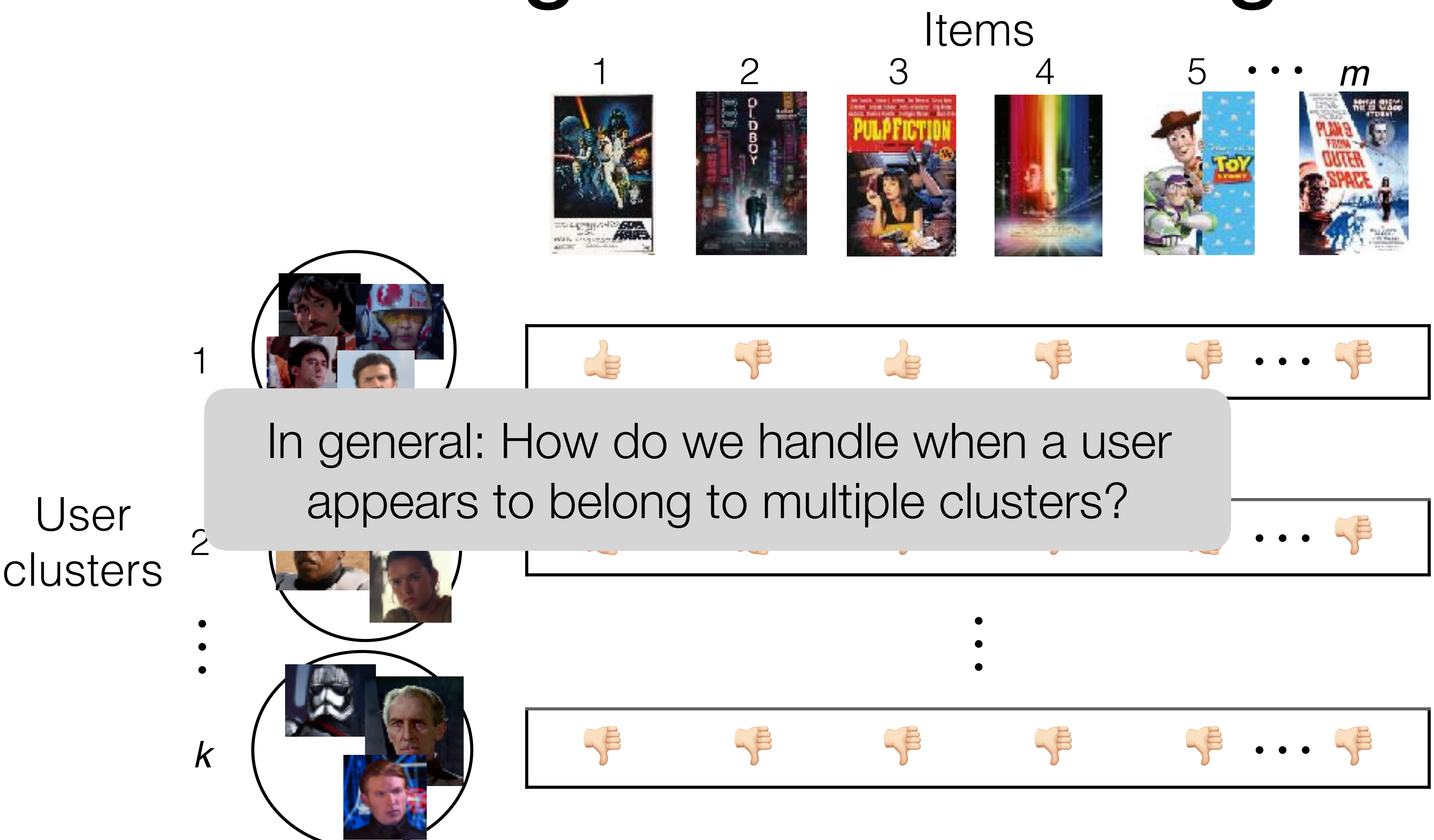
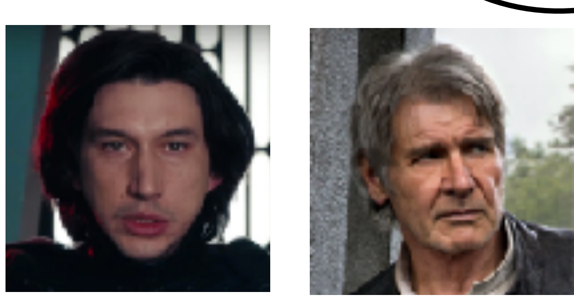


In general: How do we handle when a user appears to belong to multiple clusters?



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Topic Modeling

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Movie recommendation

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(ex … s”)

In all of these examples:

- Each data point (a feature vector) is part of multiple topics
- Each topic corresponds to specific feature values in the feature vector likely appearing

Each to … words
(exar … nce”)

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Latent Dirichlet Allocation (LDA)

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- Output: what the *k* topics are (details on this shortly)

LDA Example

LDA Example

		Document	
		Alice's text	Bob's text
Topic	weather	0.1	0.5
	food	0.9	0.5

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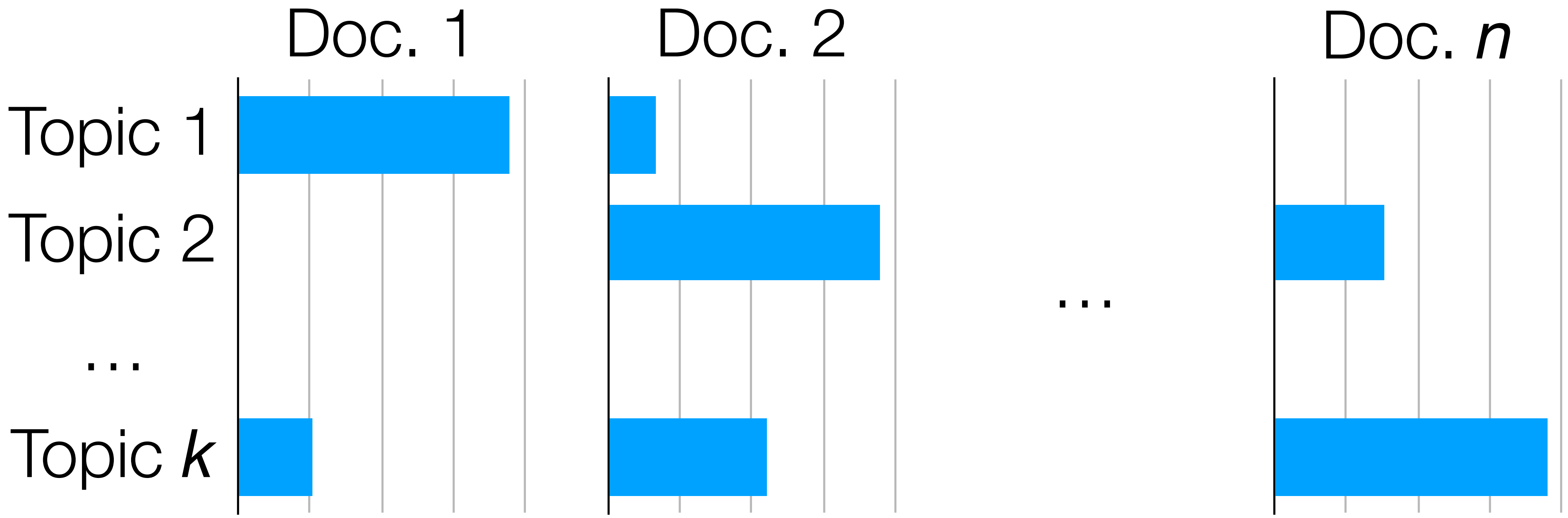
"Learning the topics" means figuring out these 4-sided coin probabilities

LDA

LDA



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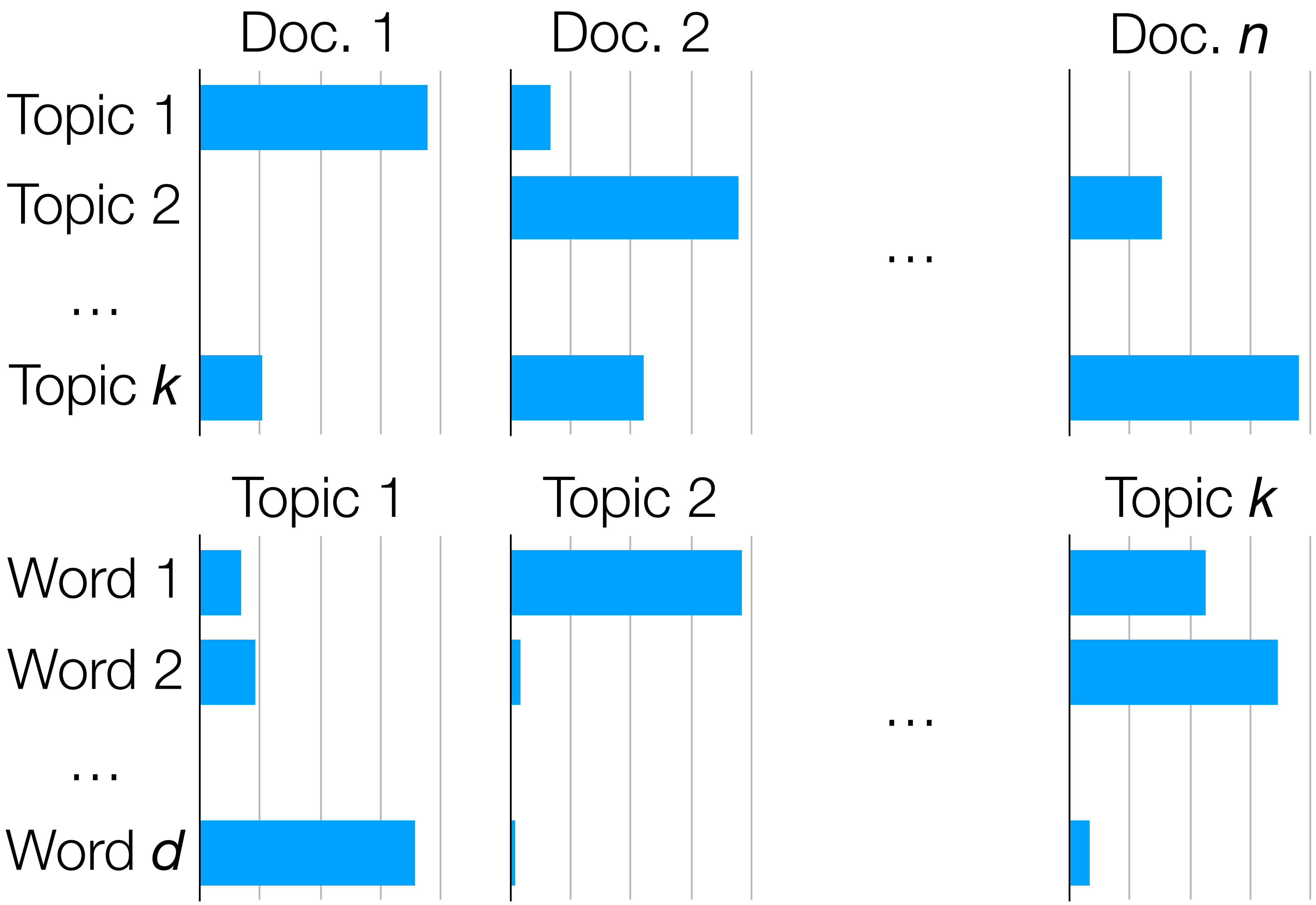
Doc. 1
Doc. 2
Doc. *n*
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Topic 2
...
Topic *k*
...
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Topic 2
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Word 2
...
Word *d*
...

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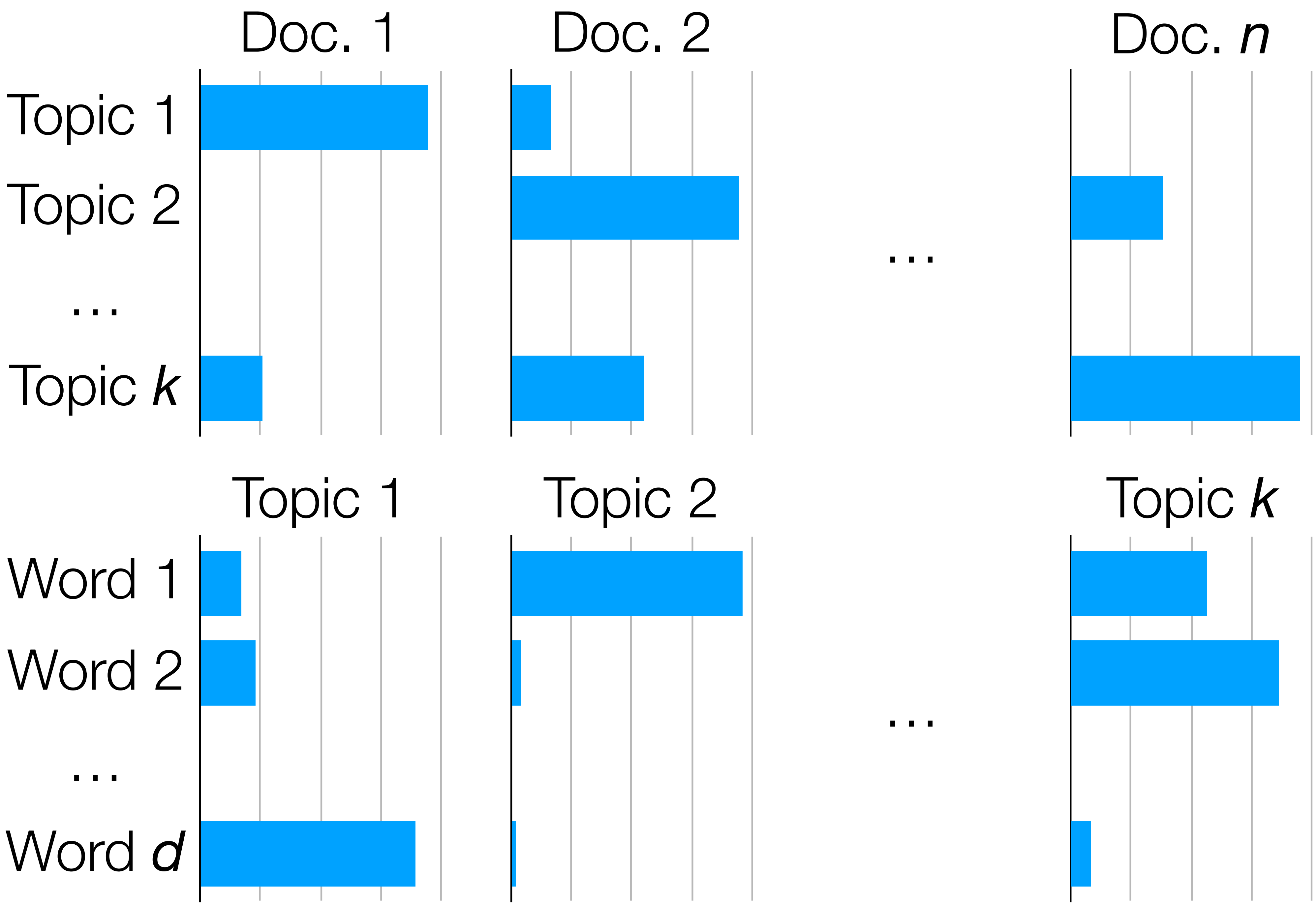

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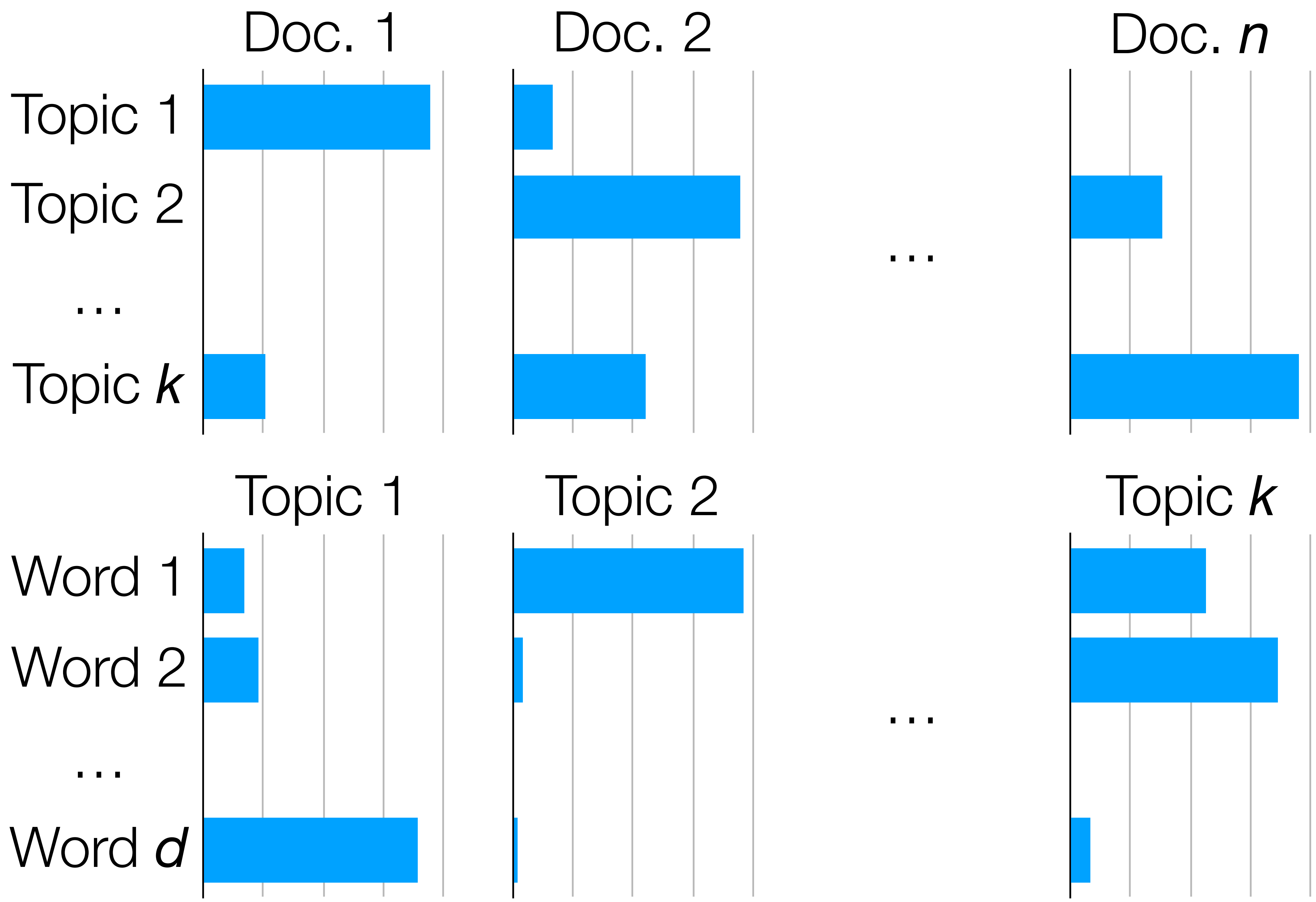

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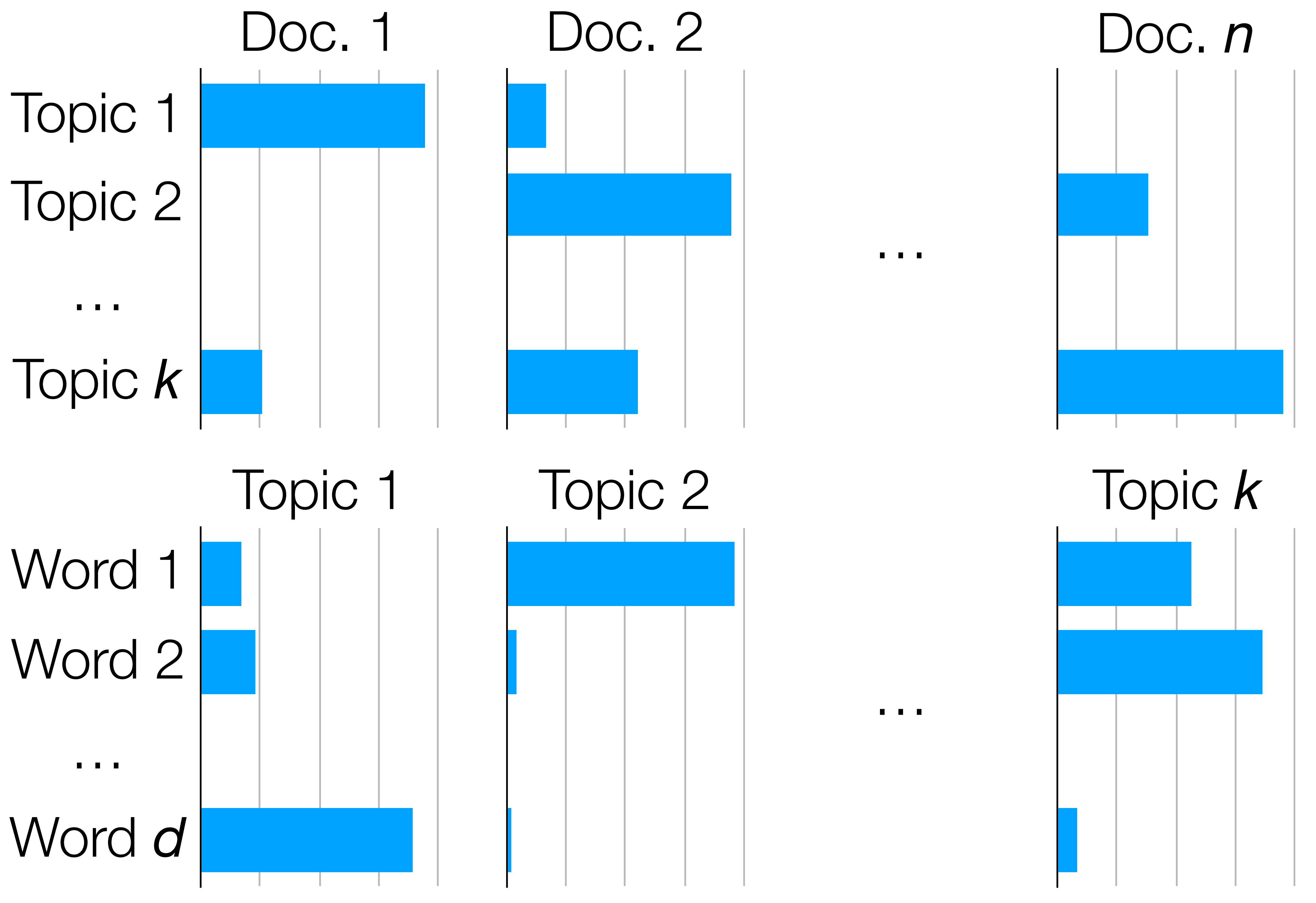

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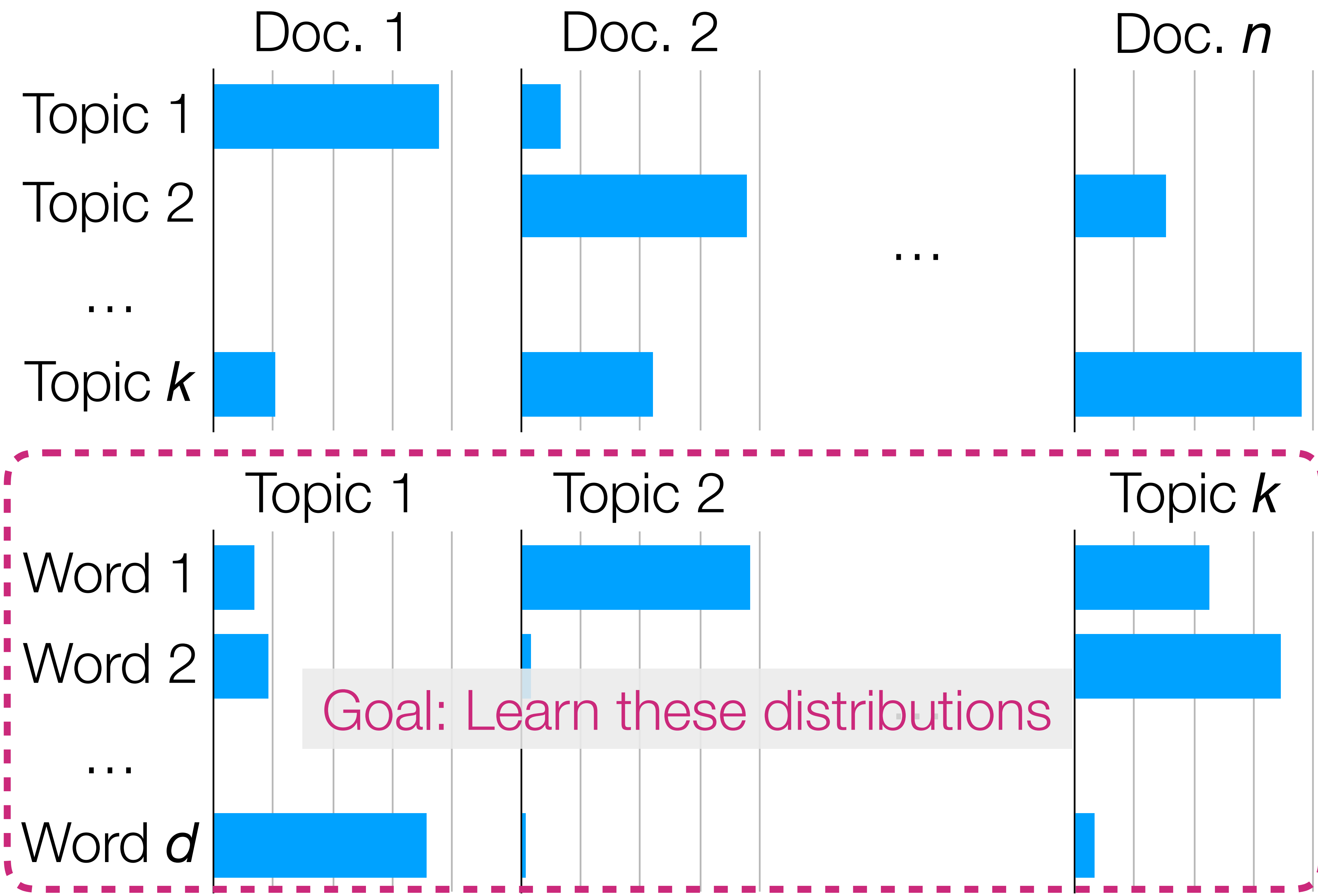

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LDA

Demo

How to Choose Number of Topics k?

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Bayesian nonparametric variant of LDA:
Hierarchical Dirichlet Process (HDP)

(similar to how we went from GMM to DP-GMM)

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Can average each of these across the topics

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- Dynamic topic models: tracks how topics change *over time*
  - This sort of idea could be used to figure out how user tastes change over time in a recommendation system
    - Could try to see if there are existing patterns for how certain topics become really popular