



[Course](#) > [5. Data Modeling](#) > [Lecture: Clustering](#) > Video

Video

🔖 [Bookmark this page](#)

When Should I Use K-Means?

[Start or transcript. Skip to the end.](#)



⋮

Now that you know what clustering is,



0:02 / 2:33



1.25x



HD



I like to buy a lot of science fiction books, history books, zombie books and the like thereof.

Video

[Download video file](#)

Transcripts

[Download SubRip \(.srt\) file](#)

[Download Text \(.txt\) file](#)

Clustering is a natural action we do even as children, by arranging similar shaped blocks and colors. K-Means clustering is best suited when you have a good idea of the number of distinct clusters your unlabeled dataset should be segmented into. Generally, the output

of K-Means is used in two ways. To separate your unlabeled data into K groups, which is the clear use case, or to find and use the resulting centroids.

Separate Your Data

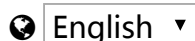
Astronomers use clustering to group different star types, classes of planets, and galaxies. Biologists use it to group every living thing by species, genus, and kingdom. In business, clustering is used to segment likely and unlikely prospects, for location assignment, factor endowment, and the assignment and deployment of remote services.

Centroid Usage

Besides divvying up samples, clustering can also provide a layer of abstraction, by directing attention to the cluster and its attributes and not each samples. In the climate change case study from the previous module, you saw how climate divisions were used as a cluster abstraction over individual ground stations for various mentioned reasons. Another example of centroid usage would be a company looking for ideal locations to open a limited number of branches, based on the location of their customers.

You can use the centroid to 'compress' your data. By referring to the centroid rather than the data sample, the number of unique values is reduced, which optimizes the execution speed of other algorithms. Isomap, for instance, uses a nearest neighbors algorithm to calculate the distance from the record you want to transform to every sample in the training dataset. By using the record-to-cluster distance approximation in replacement of the individual record-to-sample distances, since there are far fewer clusters than records, you can achieve unprecedented orders of optimization.

© All Rights Reserved



© 2012-2017 edX Inc. All rights reserved except where noted. EdX, Open edX and the edX and Open EdX logos are registered trademarks or trademarks of edX Inc. | 粤ICP备17044299号-2



