

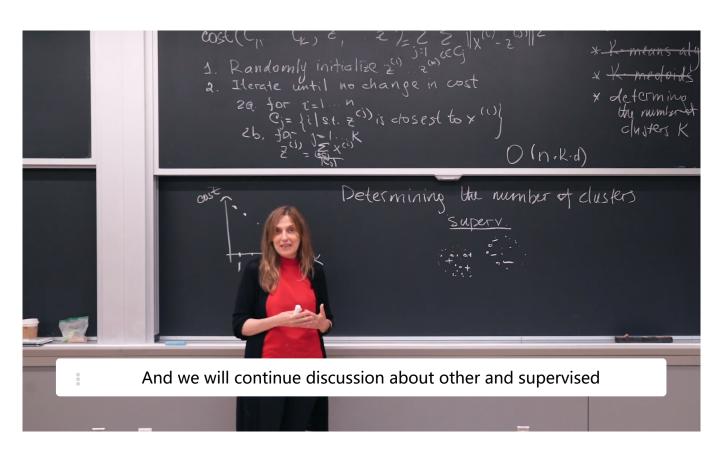
<u>Unit 4 Unsupervised Learning (2</u>

5. Motivations to well-determine

<u>Course</u> > <u>weeks</u>)

> <u>Lecture 14. Clustering 2</u> > the number of clusters K

5. Motivations to well-determine the number of clusters K Motivations to well-determine the number of clusters K



so that the clustering results is actually acceptable.

Therefore, we need to think very carefully how

to do these decision choices so that our clustering is

consistent with the expectation.

And we will continue discussion about other and supervised

technique as part of the model about generative models.

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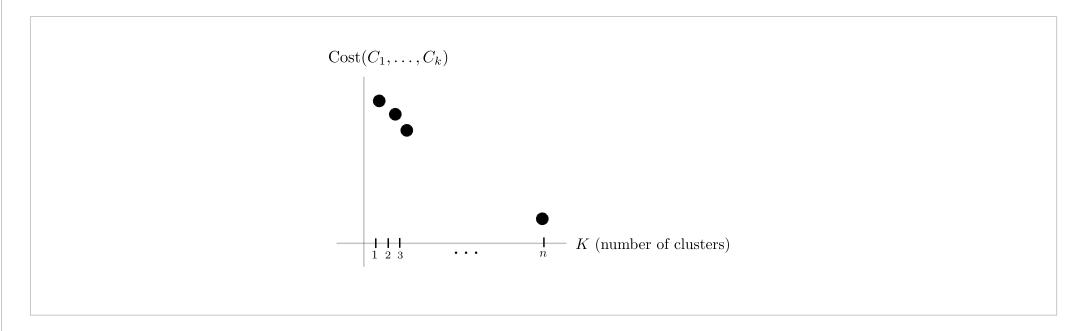
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Image Quantization Example

1/1 point (graded)

Remember that in our the first clustering lecture, the professor discussed how clustering can be used in image quantization. In short, by clustering many different colors into a few clusters, we can save(compress) the number of bits used to denote different colors.

The picture below is a general trend between the number of clusters K and the total cost of clustering.



We expect the clustering cost to decrease as we increase the number of clusters K. As mentioned in the lecture, the case of K=n is when every point is its own cluster.

In the context of image quantization, what is the problem with every point being its own cluster?

| Cost of clustering is too low |
|---|
| lacksquare The time complexity is too large when $K=n$ |
| ● There is no compression at all ✔ |
| |
| Solution: |
| When $K=n$, every point is its own cluster, which means that there is no real clustering happening.(In other words, there is no point of doing this clustering) The number of representatives is equal to the number of original colors, so no bits can be saved/compressed. |
| Submit You have used 1 of 2 attempts |
| Answers are displayed within the problem |
| Supervised Elements of Unsupervised Learning |
| 1/1 point (graded) Remember that clustering is an example of unsupervised learning. However, unlike its name suggests, there are some elements that we can "supervise" in clustering. In other words, there are some parts clustering that needs to be determined or "tuned" by us, depending or the application. Which of the following are elements of clustering that we can and should tune, depending on the application? |
| lacktriangledown Number of clusters $K lacktriangledown$ |
| $\ \square \ C_1,\ldots,C_K$, the partition of x_1,\ldots,x_n |
| $lacksquare z_1,\dots,z_K$, the representatives of each of the K clusters |
| $	extcolor{black}{f 	extcolor{f 	extcolor{black}{\color{f between}}}} \; x^{(i)} \in C_j \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	extcolor{f 	extcolor{black}{\color{f beta}}} \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	extcolor{f 	extcolor{black}{\color{f beta}}} \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	extcolor{f 	ext{black}{\color{f beta}}} \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)) \; 	ext{and} \; z_j \; ({ m dist} (x^{(i)}, z_j)$ |
| ✓ |
| Solution: |
| The number of clusters K and The cost measure for distance between $x^{(i)} \in C_j$ and z_j ($\mathrm{dist}(x^{(i)},z_j)$) are what we can control/supervise. As mentioned in the lecture, different dataset/ application context require different cost measures($\mathrm{dist}(x^{(i)},z_j)$). Also, different contexts require different optimum number of clusters. These are where you apply your domain knowledge on the application. |
| Submit You have used 1 of 3 attempts |
| Answers are displayed within the problem |
| Discussion Show Discussion |
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