

# CV Lab9 Notes

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## Prerequisites

### 1. Python packages

```
conda activate YOUR_ENV
conda install matplotlib seaborn numpy
```

### 2. K-means Visualization: <https://stanford.edu/class/engr108/visualizations/kmeans/kmeans.html>

## K-means

### 1. 牧师-村民模型:

有四个牧师去郊区布道，一开始牧师们随意选了几个布道点，并且把这几个布道点的情况公告给了郊区所有的居民，于是每个居民到离自己家最近的布道点去听课。

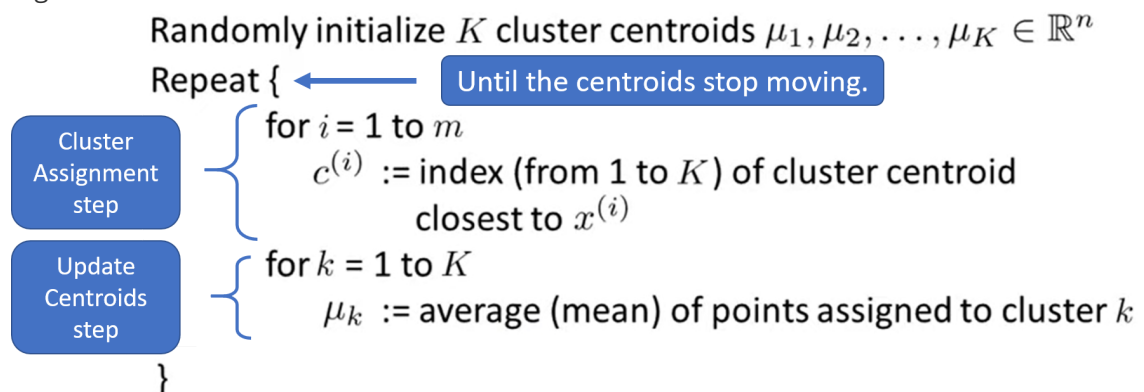
听课之后，大家觉得距离太远了，于是每个牧师统计了一下自己的课上所有的居民的地址，搬到了所有地址的中心地带，并且在海报上更新了自己的布道点的位置。

牧师每一次移动不可能离所有人都更近，有的人发现A牧师移动以后自己还不如去B牧师处听课更近，于是每个居民又去了离自己最近的布道点.....

就这样，牧师每个礼拜更新自己的位置，居民根据自己的情况选择布道点，最终稳定了下来。

### 2. Visualization demo

### 3. Algorithm



### 4. Shortcoming

- Highly depends on the initialization of  $K$  centroids, which may lead to arbitrarily bad clustering.

# K-means ++

## 1. Algorithm

### 2.2 The k-means++ algorithm

We propose a specific way of choosing centers for the **k-means** algorithm. In particular, let  $D(x)$  denote the shortest distance from a data point to the closest center we have already chosen. Then, we define the following algorithm, which we call **k-means++**.

- 1a. Take one center  $c_1$ , chosen uniformly at random from  $\mathcal{X}$ .
- 1b. Take a new center  $c_i$ , choosing  $x \in \mathcal{X}$  with probability  $\frac{D(x)^2}{\sum_{x \in \mathcal{X}} D(x)^2}$ .
- 1c. Repeat Step 1b. until we have taken  $k$  centers altogether.
- 2-4. Proceed as with the standard **k-means** algorithm.

## Reference

1. [https://www.youtube.com/watch?v=hDmNF9JG3lo&ab\\_channel=MITOpenCourseWare](https://www.youtube.com/watch?v=hDmNF9JG3lo&ab_channel=MITOpenCourseWare)
2. Forgy, E. W. (1965). Cluster analysis of multivariate data: efficiency versus interpretability of classifications. *biometrics*, 21, 768-769.
3. [https://en.wikipedia.org/wiki/K-means\\_clustering](https://en.wikipedia.org/wiki/K-means_clustering)
4. <https://en.wikipedia.org/wiki/K-means%2B%2B>
5. Arthur, David, and Sergei Vassilvitskii. *k-means++: The advantages of careful seeding*. Stanford, 2006.