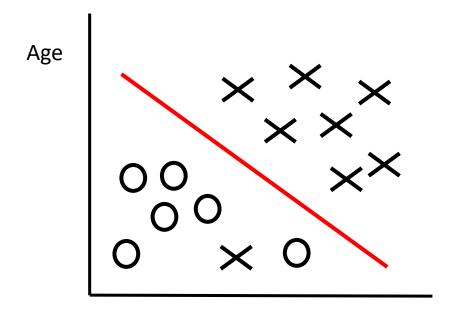
# Clustering

Prof. Dr. Christina Bauer christina.bauer@th-deg.de

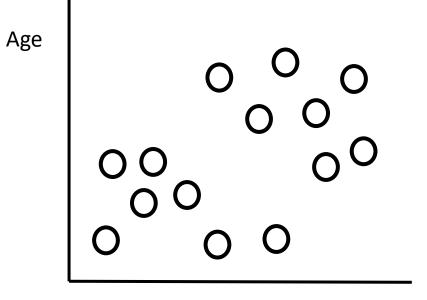
Faculty of Computer Science

#### supervised



**Tumour Size** 

#### unsupervised



**Tumour Size** 

Training set  $\{(x^1, y^1), ..., (x^m, y^m)\}$ 

# 

#### **Clustering algorithm**

Hotel quarantine: 'It'll cost us thousands and we'll be miles from home'

BBC News · 2 hours ago

- Inside a quarantine hotel on Heathrow's 'Isolation Row'
- The Independent 3 hours ago
- Coronavirus in the UK: Quarantine loophole still exists just hours before hotel policy begins, says Michael Matheson

Edinburgh News · 22 hours ago

Hotel quarantine is another example of too little too late – it's all up to immigration
officials now

The Independent · Yesterday · Opinion

· Covid vaccine rollout 'an unbelievable effort' - Johnson

BBC News · 15 hours ago





news.google.com/



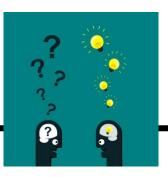




#### Coronavirus in the UK: Quarantine loophole still exists just hours before hotel policy begins, says Michael Matheson

Scottish Transport Secretary Michael Matheson has admitted a quarantine "loophole" allowing overseas travellers to avoid self-isolation still exists — less than a day before the policy comes into force.

- Data centre management: Organize computer cluster
- Social science: Social network analysis
- Market segmentation based on costumer data
- Astronomical data analysis e. g. "how are galaxies formed"



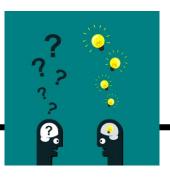
Which of the following statements are true? Check all that apply.

A: In unsupervised learning, the training set is of the form  $\{x^{(1)}, x^{(2)}, ..., x^{(m)}\}$  without labels  $y^{(i)}$ .

B: Clustering is an example of unsupervised learning.

C: In unsupervised learning, you are given an unlabeled dataset and are asked to find "structure" in the data.

D: Clustering is the only unsupervised learning algorithm.



Which of the following statements are true? Check all that apply.

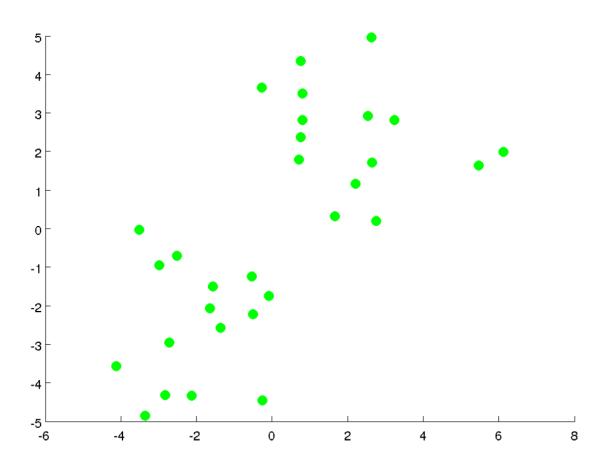
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Clustering is an example of unsupervised learning.

In unsupervised learning, you are given an unlabeled dataset and are asked to find "structure" in the data.

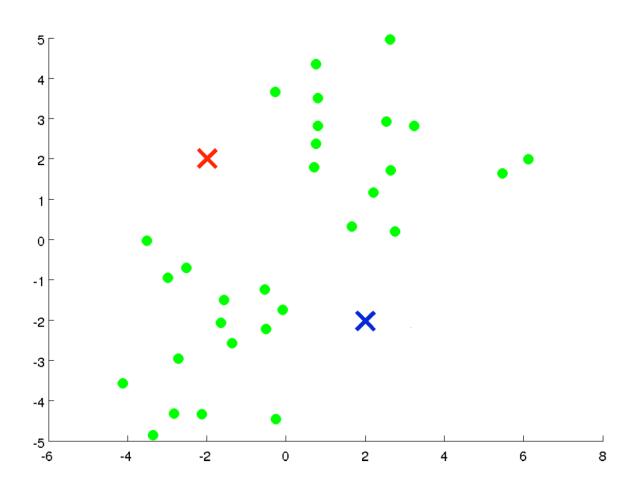
D: Clustering is the only unsupervised learning algorithm.

# K-MEANS

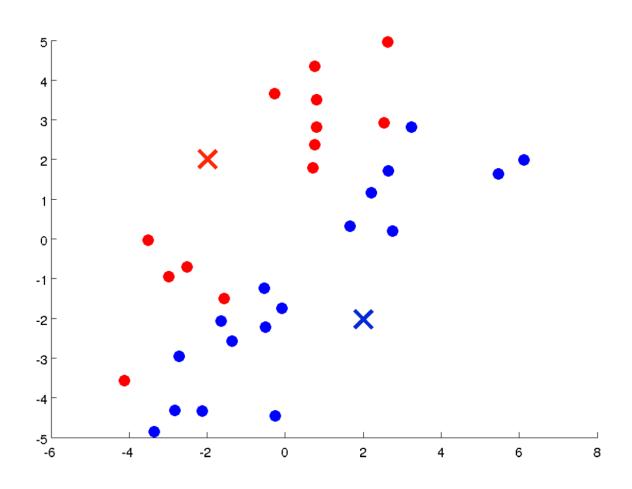


Plots by Andrew Ng

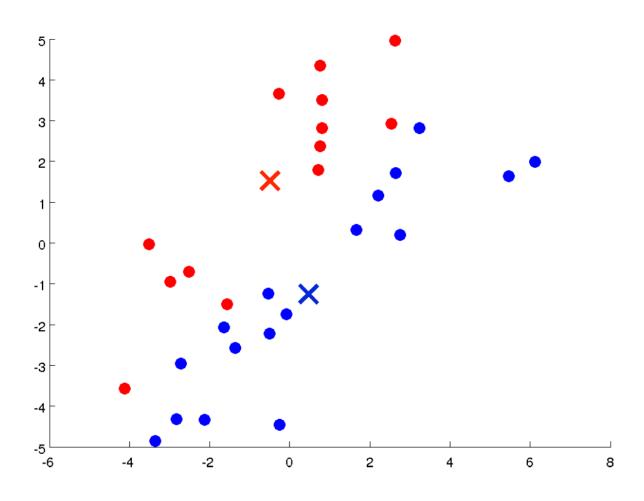
# K-MEANS — CLUSTER CENTROIDS



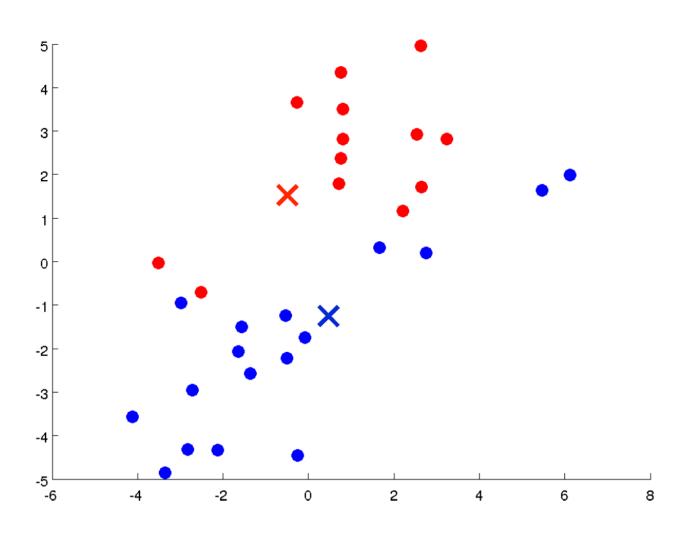
# K-MEANS — ASSIGN DATA POINTS TO CLUSTER CENTROIDS



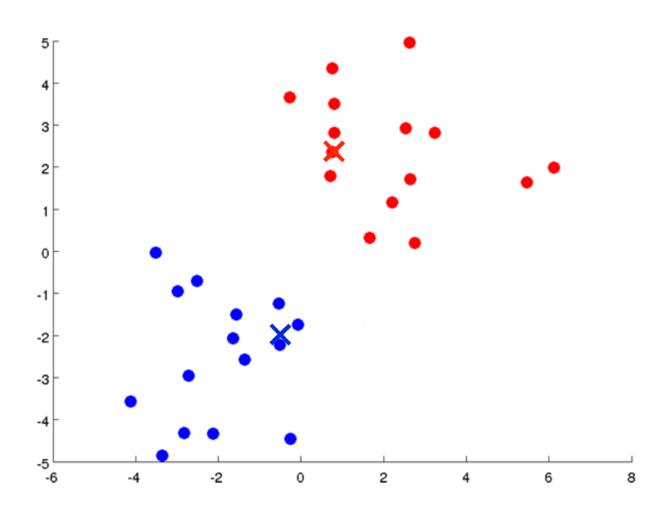
# K-MEANS — MOVE TO AVERAGE OF POINTS OF SAME COLOUR



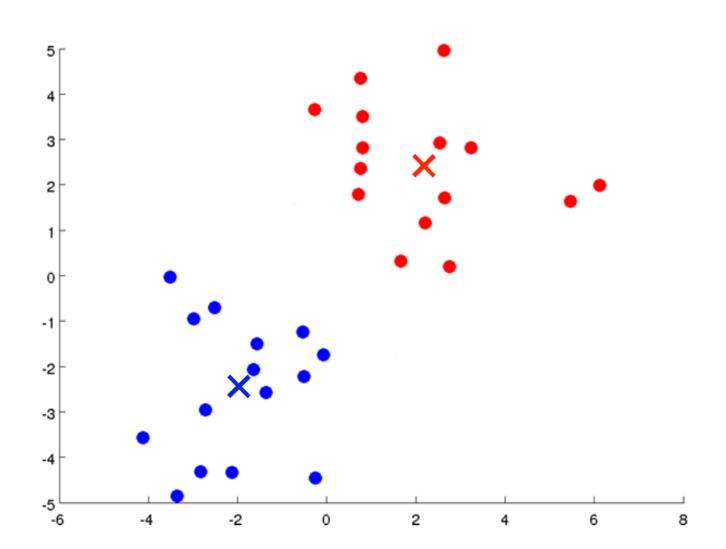
# K-MEANS — ASSIGN DATA POINTS TO "NEW" CLUSTER CENTROIDS



# K-MEANS — MOVE AND ASSIGN



# K-Means — move and Assign — no change - Done



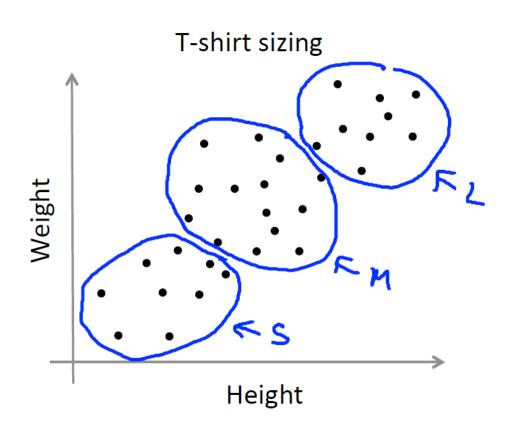
#### K-MEANS

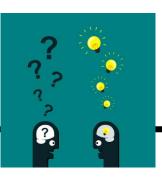
- Input:
  - K (number of clusters)
  - Training set  $\{x^{(1)}, x^{(2)}, ..., x^{(m)}\}$
- $X^{(1)} \in \mathbb{R}^n$  (no  $x_0 = 1$  convention, so not  $\mathbb{R}^{n+1}$ )

#### K-MEANS

```
Randomly initialize K cluster centroids \mu_1, \mu_2, ..., \mu_K \in \mathbb{R}^n
Repeat
                                                                                                                                  Cluster assignment
                                                                                                                                  step
                                                                                                                                  Min_{k} \| x^{(i)} - \mu_{K} \|^{2}
for i = 1 to m
                                                                                                                                  Set this value as c(i)
            c^{(i)} := index (from 1 to K) of cluster centroids closest to <math>x^{(i)}
for k = 1 to K
                                                                                                                                  Move centroid
            \mu_K := average (mean)of points assigned to cluster k
Example: c^{(1)}=2, c^{(5)}=2, c^{(6)}=2 \rightarrow \mu_K = 1/3 \ (x^{(1)}+x^{(5)}+x^{(6)}) \in \mathbb{R}^n \rightarrow \text{n-dimensional vector}
                                                                                                                                  step
```

# K-MEANS FOR NON-SEPARATED CLUSTERS





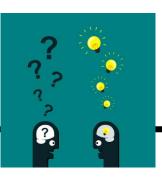
Suppose you run k-means and after the algorithm converges, you have:  $c^{(1)}=3,c^{(2)}=3,c^{(3)}=5,...$  Which of the following statements are true? Check all that apply.

A: The third example  $x^{(3)}$  has been assigned to cluster 5.

B: The first and second training examples  $x^{(1)}$  and  $x^{(2)}$  have been assigned to the same cluster.

C: The second and third training examples have been assigned to the same cluster.

D: Out of all the possible values of  $k \in \{1,2,...,K\}$  the value k=3 minimizes  $\|x^{(2)} - \mu_k\|^2$ 



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Out of all the possible values of  $k \in \{1,2,...,K\}$  the value k=3 minimizes  $\|x^{(2)} - \mu_k\|^2$ 

#### K-MEANS OPTIMIZATION OBJECTIVE

- $c^{(i)}$  = index of cluster (1,2,..,K) to which example  $x^{(i)}$  is currently assigned
- $\mu_K$  = cluster centroid k ( $\mu_K \in \mathbb{R}^n$ ; k  $\in \{1,2,...,K\}$ )
- $\mu_c^{(i)}$  = cluster centorid of cluster to which example  $x^{(i)}$  has been assigned (e.g.  $x^{(i)} \rightarrow 5$  i.e.  $c^{(i)} = 5$  i.e.  $\mu_c^{(i)} = \mu_5$ )

Optimization objective:

$$\begin{split} J(c^{(1)},...,c^{(m)},\mu_1,...,\mu_K) &= \frac{1}{m} \sum_{i=1}^m \| \ x^{(i)} - \mu_c^{(i)} \|^2 \ \ \text{(Distortion Cost Function)} \\ & \quad \text{min } J(c^{(1)},...,c^{(m)},\mu_1,...,\mu_K) \\ & \quad c^{(1)},...,c^{(m)} \\ & \quad \mu_1,...,\mu_K \end{split}$$

#### K-MEANS

```
Randomly initialize K cluster centroids \mu_1, \mu_2, ..., \mu_k \in \mathbb{R}^n
Repeat
                                                                                                Cluster assignment
                                                                                                step
                                                                                                Min J()
for i = 1 to m
                                                                                                with respect to
                                                                                                C^{(1)},...,C^{(m)}
         c^{(i)} := index (from 1 to K) of cluster centroids closest to <math>x^{(i)}
                                                                                                (holding \mu_1,...,\mu_K
                                                                                                fixed)
for k = 1 to K
                                                                                             Move centroid
          \mu_{\kappa} := average (mean)of points assigned to cluster k -
                                                                                             step
                                                                                             Minimize J() with
                                                                                             respect to \mu_1,...,\mu_K
```



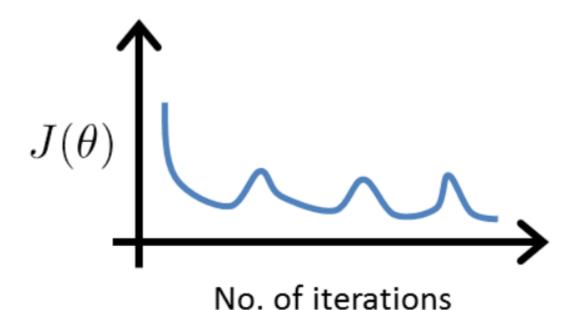
Suppose you have implemented k-means and to check that it is running correctly, you plot the cost function  $J(c^{(1)},...,c^{(m)},\mu_1,...,\mu_K)$  as a function of the number of iterations. You get the given plot. What does this mean?

A: The learning rate is too large.

B: The algorithm is working correctly.

C: The algorithm is working, but k is too large.

D: It is not possible for the cost function to sometimes increase. There must be a bug in the code.





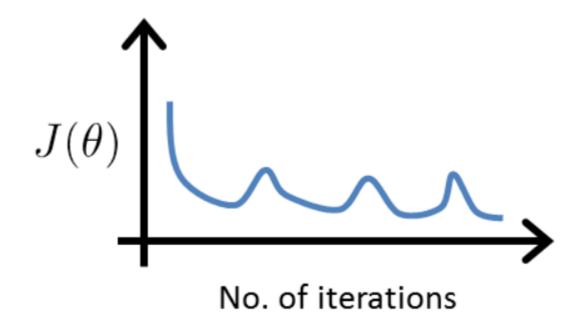
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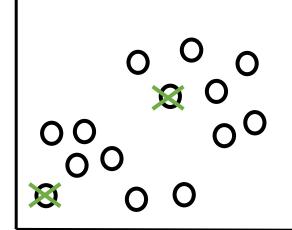
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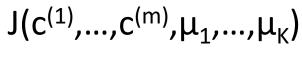


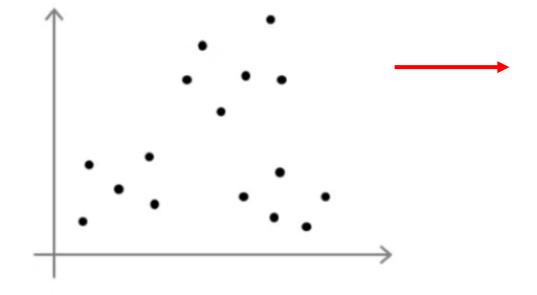
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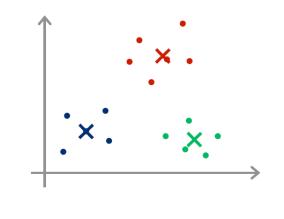
- Should have K<m</li>
- Randomly pick K training examples
- Set  $\mu_1,...,\mu_K$  equal to these K examples

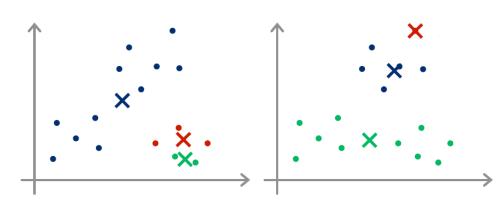


# Local optima of



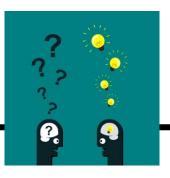






```
For i = 1 to 100  \{ \\ \text{Randomly initialize k-means.} \\ \text{Run k-means.} \\ \text{Get } c^{(1)},...,c^{(m)},\mu_1,...,\mu_K. \\ \text{Compute the cost function } J(c^{(1)},...,c^{(m)},\mu_1,...,\mu_K). \\ \}
```

 $\rightarrow$  Pick the clustering with the lowest cost  $J(c^{(1)},...,c^{(m)},\mu_1,...,\mu_K)$ .



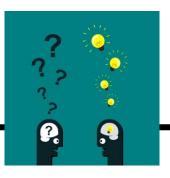
Which of the following is the recommended way to initialize k-means?

A: Pick a random integer i from  $\{1,...,k\}$ . Set  $\mu_1 = \mu_2 = ... = \mu_k = x^{(i)}$ .

B: Pick k distinct random integers  $i_1,...,i_k$  from  $\{1,...,k\}$ . Set  $\mu_1 = x^{(1)}, \mu_2 = x^{(2)},...,\mu_k = x^{(k)}$ .

C: Pick k distinct random integers  $i_1,...,i_k$  from  $\{1,...,m\}$ . Set  $\mu_1 = x^{(1)}, \mu_2 = x^{(2)},...,\mu_k = x^{(k)}$ .

D: Set every element of  $\mu_i \in \mathbb{R}^n$  to a random value between  $-\epsilon$  and  $\epsilon$  for some small  $\epsilon$ .



Which of the following is the recommended way to initialize k-means?

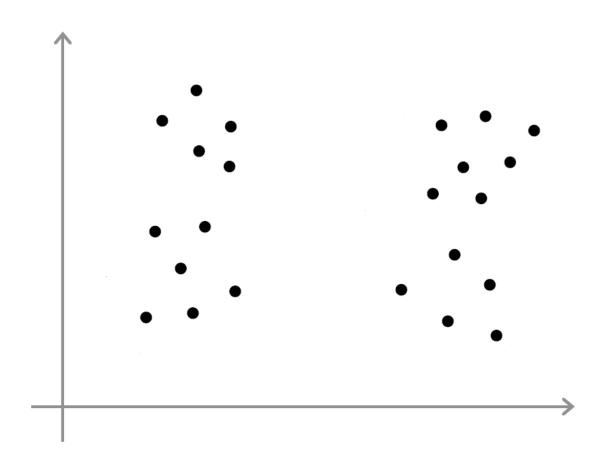
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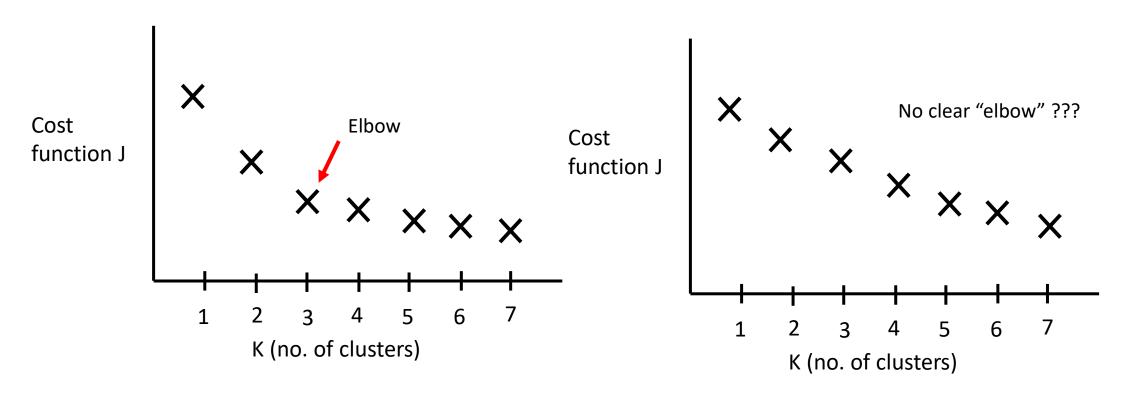
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D: Set every element of  $\mu_i \in \mathbb{R}^n$  to a random value between  $-\epsilon$  and  $\epsilon$  for some small  $\epsilon$ .

# How many clusters do you see?



# What is the right value of k? Elbow Method





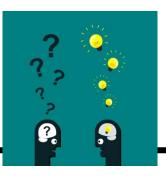
Suppose you run k-means using k = 3 and k = 5. You find that the cost function J is much higher for k = 5 than for k = 3. What can you conclude?

A: This is mathematically impossible. There must be a bug in the code.

B: The correct number of clusters is k = 3.

C: In the run with k = 5, k-means got stuck in a bad local minimum. You should try re-running k-means with multiple random initializations.

D: In the run with k = 3, k-means got lucky. You should try re-running k-means with k = 3 and different random initializations until it performs no better than with k = 5.



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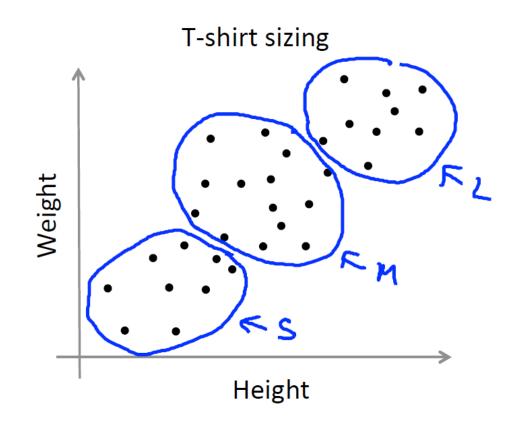
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#### CHOOSING THE VALUE OF K

- Often you use k-means to get clusters for a later purpose
- Evaluate your clusters based on this purpose
- Example:
  - How many t-shirt clusters do I want to have?
  - K = 3: easier to produce
  - K = 5: better fit for the customers



For which of the following tasks might K-means clustering be a suitable algorithm? Select all that apply.

A: Given a set of news articles from many different news websites, find out what are the main topics covered.

B: Given historical weather records, predict if tomorrow's weather will be sunny or rainy.

C: Given many emails, you want to determine if they are Spam or Non-Spam emails.

D: From the user usage patterns on a website, figure out what different groups of users exist.

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Suppose we have three cluster centroids  $\mu_1$ =[1;2],  $\mu_2$ =[-3;0], and  $\mu_3$ =[4;2]. Furthermore, we have a training example  $x^{(i)}$ =[-2;1]. After a cluster assignment step, what will  $c^{(i)}$ ?

A: 
$$c^{(i)} = 3$$
.

B: c<sup>(i)</sup> is not assigned.

C: 
$$c^{(i)} = 1$$

D: 
$$c^{(i)} = 2$$

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$$\mu_1 = [1;2] \rightarrow [-2;1] - [1;2] = |[-3,-1]|$$
 $\mu_2 = [-3;0] \rightarrow [-2;1] - [-3;0] = |[1,1]|$ 
 $\mu_3 = [4;2] \rightarrow [-2;1] - [4;2] = |[-6,-1]|$ 

K-means is an iterative algorithm, and two of the following steps are repeatedly carried out in its inner-loop. Which two?

A: The cluster centroid assignment step, where each cluster centroid  $\mu_i$  is assigned (by setting  $c^{(i)}$ ) to the closest training example  $x^{(i)}$ .

B: Move each cluster centroid  $\mu_k$  by setting it to be equal to the closest training example  $x^{(i)}$ .

C: The cluster assignment step, where the parameters c(i) are updated.

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#### REMINDER: K-MEANS

```
Randomly initialize K cluster centroids \mu_1, \mu_2, ..., \mu_k \in \mathbb{R}^n
Repeat
                                                                                                                                  Cluster assignment
                                                                                                                                  step
                                                                                                                                  Min_{k} \| x^{(i)} - \mu_{K} \|^{2}
for i = 1 to m
                                                                                                                                  Set this value as c(i)
            c^{(i)} := index (from 1 to K) of cluster centroids closest to <math>x^{(i)}
for k = 1 to K
                                                                                                                                  Move centroid
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Example: c^{(1)}=2, c^{(5)}=2, c^{(6)}=2 \rightarrow \mu_K = 1/3 \ (x^{(1)}+x^{(5)}+x^{(6)}) \in \mathbb{R}^n \rightarrow \text{n-dimensional vector}
                                                                                                                                  step
```

Suppose you have an unlabeled dataset  $\{x^{(1)},...,x^{(m)}\}$ . You run K-means with 50 different random initializations, and obtain 50 different clusterings of the data. What is the recommended way for choosing which one of these 50 clusterings to use?

A: The answer is ambiguous, and there is no good way of choosing.

B: For each of the clusterings, compute  $\frac{1}{m}\sum_{i=1}^{m}\|\mathbf{x}^{(i)}-\boldsymbol{\mu}_{\mathbf{c}}^{(i)}\|^2$  and pick the one that minimizes this.

C: Always pick the final (50th) clustering found, since by that time it is more likely to have converged to a good solution.

D: The only way to do so is if we also have labels  $y^{(i)}$  for our data.

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Which of the following statements are true? Select all that apply.

A: If we are worried about K-means getting stuck in bad local optima, one way to reduce this problem is if we try using multiple random initializations.

B: For some datasets, the "right" or "correct" value of K (the number of clusters) can be ambiguous, and hard even for a human expert looking carefully at the data to decide.

C: The standard way of initializing K-means is setting  $\mu_1$ =...= $\mu_k$  to be equal to a vector of zeros.

D: Since K-Means is an unsupervised learning algorithm, it cannot overfit the data, and thus it is always better to have as large a number of clusters as is computationally feasible.

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