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Assignment 6

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1 0/1 0 maint/crue de di
1.0/1.0 point (graded) The <i>K</i> -means algorithm is a/an
Supervised learning algorithm
Unsupervised learning algorithm
Reinforcement learning algorithm
O Deep learning algorithm
✓
Submit
2
1.0/1.0 point (graded) Unsupervised learning
O Both data and labels
Neither data nor labels
Cabels but not data
Requires data, but NO labels
· ·
Submit
Submit 3
3 1.0/1.0 point (graded)
3
3 1.0/1.0 point (graded) The cluster assignment indicator $\alpha_4(5)$
3 1.0/1.0 point (graded) The cluster assignment indicator $\alpha_4(5)$ Equals 0 when $\overline{x}(5)$ belongs to C_4 and 1 otherwise
3 1.0/1.0 point (graded) The cluster assignment indicator $\alpha_4(5)$ Equals 0 when $\overline{x}(5)$ belongs to C_4 and 1 otherwise Equals 1 when $\overline{x}(4)$ belongs to C_5 and 0 otherwise
3 1.0/1.0 point (graded) The cluster assignment indicator $\alpha_4(5)$ Equals 0 when $\overline{x}(5)$ belongs to C_4 and 1 otherwise Equals 1 when $\overline{x}(4)$ belongs to C_5 and 0 otherwise Equals 0 when $\overline{x}(4)$ belongs to C_5 and 1 otherwise

1.0/1.0 point (graded) The K-means algorithm is imported in PYTHON as
from sklearn.algorithms import KMeans
from sklearn import KMeans
from sklearn.cluster import KMeans
from sklearn.datasets import KMeans
✓
Submit
5
1.0/1.0 point (graded)
The metric used to determine the number of clusers for K-means is SSE
Confusion probability
R2 score
Probability of error
✓
Submit
6
1.0/1.0 point (graded) To generate the clusters in PYTHON we employ
from sklearn.datasets import make_clusters
from sklearn import make_blobs
from sklearn.datasets import make_blobs
from sklearn import make_clusters
✓
Submit
7
1.0/1.0 point (graded) The K -means cost-function to minimize is given as
$\sum_{i=1}^{K} \sum_{j=1}^{M} \alpha_{i}(j) \ \overline{x}(j) - \overline{\mu}_{i} \ $

$ \sum_{i=1}^{K} \sum_{j=1}^{M} \alpha_i(j) \ \overline{x}(j) - \overline{\mu}_i\ ^2 $
$\sum_{i=1}^{K} \sum_{j=1}^{M} \alpha_{i}(j) \left(\overline{x}(j) - \overline{\mu}_{i}\right) \left(\overline{x}(j) - \overline{\mu}_{i}\right)^{T}$
$\bigcap_{i=1}^K \alpha_i(j) \ \overline{x}(j) - \overline{\mu}_i\ ^2$
•
Submit
8 1.0/1.0 point (graded)
To determine the cluster in iteration <i>l</i> ,
We assign $\overline{x}(j)$ to the farthest centroid $\overline{\mu}_{\widetilde{i}}^{(l-1)}$
We assign $\overline{x}(j)$ to the centroid $\frac{\sum\limits_{j:\overline{x}(j)\in\mathcal{C}_i}\overline{x}(j)}{\sum\limits_{j:\overline{x}(j)\in\mathcal{C}_i}1}$
We assign $\overline{x}(j)$ to the centroid $\frac{\sum\limits_{j:\overline{x}(j)\in\mathcal{E}_i}\overline{x}(j)}{M}$
We assign $\overline{x}(j)$ to the closest centroid $\overline{\mu_i}^{(l-1)}$
Submit
9
1.0/1.0 point (graded) The centroids for the given clusters can be determined as
$ \begin{array}{c} \sum_{j:\bar{x}(j)\in\mathcal{C}_i} \bar{x}(j) \\ \underline{M} \end{array} $
$ \underbrace{\sum_{j: \overline{x}(j) \in \mathcal{C}_i} \overline{x}(j)}_{j: \overline{x}(j) \in \mathcal{C}_i} $
$ \begin{array}{c} \sum_{\substack{j:\bar{x}(j)\in\mathcal{C}_i\\K}} \bar{x}(j) \\ \hline K \end{array} $
$ \begin{array}{ccc} & \sum_{j} \overline{x}(j) \\ & M \end{array} $

M		
✓		
Submit		
0		
0/1.0 point (graded)		
e centroids of the clusters are	determined as	
Average of all points assign	ned to cluster i in iteration l	
<u> </u>		
Average of all points assign	ned to all clusters in iteration <i>l</i>	
Average of only the new po	oints assigned to cluster i in iteration l	
Average of outliers assigne	ed to cluster i in iteration l	
✓		
Submit		

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