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Review1 COSC 4335 Spring 2017[[1]](#footnote-1)

1. What is the main difference between ordinal and a nominal attributes?

*The values of ordinal attributes are ordered; this fact has to be considered when assessing similarity between two attribute values!*

1. What role does exploratory data analysis play in a data mining project?

**create background knowledge about the dataset and the task at hand [1], assess difficulty [1], provide knowledge to help select appropriate tools for the task[1], assess quality of data [1], validate data [1], help to form hypothesis [1], find issues, patterns and errors in data [1]**

1. What does the size of the box of a boxplot measure; what statistical measure is it related to?

*The difference between the 25thand 75th quantile, also called IQR, of the attribute; the size of the box is used as an estimator of the standard deviation of the attribute.*

1. A R-boxplot (also called Turkey boxplots) of an attribute A has whiskers at 2 and 10; what does this tell you about attribute A? What attribute values are typically considered to be outliers in boxplots?

*The largest attribute value that is not an outlier is 10, and the smallest attribute value that is not an outlier is 2; all attribute values that are 1.5IQR or more above the 25% quantile or 1.5IQR below the the 75% quantile of the attribute are considered outliers.*

1. Assume we have a dataset in which the median of the first attribute is twice as large as the mean of the first attribute? What does this tell you about the distribution of the first attribute?

*It is skewed,…*

1. What is (are) the characteristic(s) of a good histogram (for an attribute)?

*It captures the most important characteristics of the underlying density function*

1. Interpret the following 2 histograms and their relationships which describe the male and female age distribution in the US, based on Census Data.



**Both histograms: curves are continuous with no gabs or outliers, and somewhat smooth[1], bimodal with 2 (1??; 0??) not well separated maxima at 5-19 and 35-44 [1.5], values significantly drop beyond age 55[1]🡪skewed distribution**

**Comparison: Curves are somewhat similar until age 55 [1] (although there are more males initially [0.5]); decline in the male curve is significantly steeper---women live longer[1].** Other observations might receive credit; points will be subtracted if you write things which do not make any sense or are false.

1. Assume you find out that two attributes have a correlation of 0.02; what does this tell you about the relationship of the two attributes? Answer the same question assuming the correlation is -0.98!

*0.02:= no linear relationships exists between the two attributes—but other relationships might exist; 0.98:=a strong linear relationship exists—if the value of one attribute goes up the value of the other goes down*

1. What of the following cluster shapes K-means is capable to discover? a) triangles b) clusters inside clusters c) the letter ‘T ‘d) any polygon of 5 points e) the letter ’I’

In general, the shapes k-means can discover are convex polygons; consequently, it can only discover triangles and clusters if the shape of the depicted letter I; it will not be able to discover shapes of concave polygons of 5 points!

concave polygon

1. What are the characteristics of clusters K-Medoids/K-means are trying to find? What can be said about the optimality of the clusters they find? Both algorithms a sensitive to initialization; explain why this is the case!

**Looking for: compact clusters [1] which minimize the MSE/SSE fitness function[1]**

**Suboptimal, local minima of the fitness function [1]**

**Employ hill climbing procedures which climb up the hill the initial solution belongs to; therefore, using different seeds which are on the foot of different hills (valleys) will lead to obtaining different solutions which usually differ in quality [2].**

1. K-means is probably the most popular clustering algorithm; why do you believe is this the case?

Fast; runtime complexity is basically O(n); also saves time by minimizing an “implicit” objective function

Easy to use; no complex parameter values have to be selected…

Its properties are well understood!

Can deal with high-dimensional datasets

The properties of clusters can be “tweaked” by using different kind of distance functions/Kernel approaches

1. Assume the following dataset is given: (2,2), (4,4), (5,5), (6,6), (8,8),(9,9), (0,4), (4,0) . K-Means is used with k=4 to cluster the dataset. Moreover, Manhattan distance is used as the distance function (formula below) to compute distances between centroids and objects in the dataset. Moreover, K-Means’s initial clusters C1, C2, C3, and C4 are as follows:

C1: {(2,2), (4,4), (6,6)}

C2: {(0,4), (4,0)}

C3: {(5,5), (9,9)}

C4: {(8,8}}

Now K-means is run for a single iteration; what are the new clusters and what are their centroids?[[2]](#footnote-2) [5]

**d((x1,x2),(x1’,x2’))= |x1-x1’| + |x2-x2| Manhattan Distance**

**Centroids:**

**c1: (4, 4)**

**c2: (2, 2)**

**c3: (7, 7)**

**c4: (8, 8)**

**Clusters:**

**C1 = {(4, 4), (5, 5)}**

**C2 = {(2, 2), (0, 4), (4, 0)} assigning (0,4) and (4,0) to cluster C1 is also correct!**

**C3 = {(6, 6)}**

**C4 = {(8, 8), (9, 9)}**

1. Assume we apply K-medoids for k=3 to a dataset consisting of 5 objects numbered 1,..5 with the following distance matrix:

Distance Matrix:

0 2 4 5 1 🡨object1

 0 2 3 3

 0 1 5

 0 2

 0

 The current set of representatives is {1,3,4}; indicate all computations k-medoids (PAM)

performs in its next iteration!

*The following cluster is formed: {1,2,5} {3} {4} or {1,5} {2,3} {4} as object 2 has the same distance of 2 to representatives 1 and 3. Let us assume {1,5} {2,3} 5 is selected as the current cluster its SSE is:*

*1\*\*2+2\*\*2=5; in the next iteration six clusters for representative sets {2,3,4}, {5,3,4},{1,2,4},{1,5,4},{1,3,2},{1,3,5} and the cluster with the lowest SSE is selected, which is*

*{1,5} {2} {4,3} which orginated from the representative set {1,2,4}[[3]](#footnote-3); it has a SSE of 1\*\*+1\*\*2=2 and as it is better than the cluster of the previous iteration it becomes the new current cluster and the algorithm continues for at least one more iteration.*

14. What are the characteristics of a border point in DBSCAN?

*A borderpoint is a non-corepoint that is within the radius of a corepoint!*

15. How does DBSCAN form clusters?

No answer given!

16. Assume I run DBSCAN with MinPoints=6 and epsilon=0.1 for a dataset and I obtain 4 clusters and 5% of the objects in the dataset are classified as outliers. Now I run DBSCAN with MinPoints=8 and epsilon=0.1. How do expect the clustering results to change?

**The number of core points likely will decrease and the number of outliers likely will increase; some clusters might cease to exist; other clusters might be broken up into a set of smaller clusters; it is hard to say, if the number of clusters increases/decreases after increasing the number of MinPoints.**

17. Hierarchical Clustering algorithm creates dendrograms; what is a dendogram? How are the clustering results K-means creates differerent from those of hierarchichal clustering algorithms?

*A* ***dendrogram*** *(from* [*Greek*](https://en.wikipedia.org/wiki/Greek_language) *dendro "tree" and gramma "drawing A dendrogram (from Greek dendro "tree" and gramma "drawing") is a tree diagram frequently used to illustrate the arrangement of the clusters produced by hierarchical clustering) is a* [*tree*](https://en.wikipedia.org/wiki/Tree_%28graph_theory%29) *diagram frequently used to illustrate the arrangement of the clusters produced by* [*hierarchical clustering*](https://en.wikipedia.org/wiki/Hierarchical_clustering)*. Edges of the dendrogram represent split/merge relationships between the nodes of the tree which represent clusters.*

K-means creates a single clustering; hierarchical clustering creates multiple clusterings, namely a set (of nested) clusterings.

Tutorial Exercises(see <http://www2.cs.uh.edu/~ceick/UDM/Clustering_Exercises1.pdf>

18. Tutorial Exercise 3

See solution in the pdf-file!

19. Tutorial Exercise 5

See solution in the pdf-file!

1. Some of the problems have been discussed in the lecture on March 2, 2017. [↑](#footnote-ref-1)
2. If there are any ties, break them whatever way you want! [↑](#footnote-ref-2)
3. The one that originates from {1, 3, 2} is identical and therefore equally good. [↑](#footnote-ref-3)