Esercises on Clustering

Exercise. Show that the L_1 (Euclidean) and Edit distances satisfy the four requirements for a metric space.

Solution. Recall that given a set M with distance function $d(\cdot)$, (M, d) is a metric space if the following conditions hold for any $x, y, x \in M$:

- 1. $d(x,y) \ge 0$;
- 2. d(x,y) = 0 if and only if x = y;
- 3. d(x,y) = d(y,x); (symmetry)
- 4. $d(x, z) \le d(x, y) + d(y, z)$; (triangle inequality)

 L_1 distance. Recall that the L_1 distance between two points $x, y \in \Re^n$ is

$$d_{L1}(x,y) = \sum_{i=1}^{n} |x_i - y_i|,$$

where the x_i 's and y_i 's denote the coordinates. We observe that for any three real numbers a, b and c, we have $|a - b| \le |a - c| + |c - b|$, which can be easily proved considering all possible relative positions of a, b and c on the line. Now we prove that the four conditions above are satisfied.

- 1. $d_{L1}(x,y) \ge 0$. It follows since all terms of the summation are ≥ 0 .
- 2. $d_{L1}(x,y) = 0$ if and only if x = y. It follows since, in order for $d_{L1}(x,y)$ to be 0, all terms of the summation must be 0, hence $x_i = y_i$ for every i.
- 3. $d_{L1}(x,y) = d_{L1}(y,x)$. It follows since |a-b| = |b-a| for any two reals a and b.
- 4. $d(x,z) \leq d(x,y) + d(y,z)$. By the initial observation, we have that

$$d_{L1}(x,z) = \sum_{i=1}^{n} |x_i - z_i|$$

$$\leq \sum_{i=1}^{n} (|x_i - y_i| + |y_i - z_i|)$$

$$= (\sum_{i=1}^{n} |x_i - y_i|) + (\sum_{i=1}^{n} |y_i - z_i|)$$

$$= d_{L1}(x,y) + d_{L1}(y,z)$$

Edit distance. Recall that the edit distance is defined for strings. For any two strings X e Y, over some alphabet, $d_{\text{edit}}(X,Y)$ is the minimum number of deletions or insertions that must be applied to transform X into Y. Equivalently, it holds that

$$d_{\text{edit}}(X,Y) = |X| + |Y| - 2|\text{LCS}(X,Y)|,$$

where LCS(X,Y) is the Longest Common Subsequence in X and Y, that is, the longest string that is a subsequence of both X and Y (note that if Z is a subsequence of W, this means that the characters of Z occurr in W in the same order but, possibily, not consecutively). It is immediate to see that $|X|, |Y| \ge |LCS(X,Y)|$. Now we prove that the four conditions above are satisfied.

- 1. $d_{\text{edit}}(X,Y) \ge 0$. It follows since $|X|, |Y| \ge |\text{LCS}(X,Y)|$
- 2. $d_{\operatorname{edit}}(X,Y)=0$ if and only if X=Y. It follows since the relation $|X|,|Y|\geq |\operatorname{LCS}(X,Y)|$ implies that $d_{\operatorname{edit}}(X,Y)=0$ if and only if $|\operatorname{LCS}(X,Y)|=|X|=|Y|$, i.e., $\operatorname{LCS}(X,Y)=X=Y$.
- 3. $d_{\text{edit}}(X,Y) = d_{\text{edit}}(Y,X)$. It follows since the role of X and Y in the second definition is perfectly symmetrical.
- 4. $d_{\text{edit}}(X, Z) \leq d_{\text{edit}}(X, Y) + d_{\text{edit}}(Y, Z)$. Considering the first definition, we can transform X into Z by first transforming X into Y, and then Y into Z. Therefore, the minimum number of deletions or insertions required to transform X into Z cannot be larger than the minimum number of such operations required to transform X into Y plus the minimum number of such operations required to transform Y into Z.

Exercise. Consider a set P of N points in a metric space (M,d) and a subset $S \subseteq P$ of k centers from P. Design a 1-round MapReduce algorithm that implements Partition(P,S) with $M_L = O(k)$ and $M_A = O(N)$. Suppose that each point $x \in P$ is represented as a key-value pair $(\mathrm{ID}_x, (x, f))$, where ID_x is a distinct integer in [0, N), and f is a binary flag which is 1 if $x \in S$ and 0 otherwise. You can assume that k and N are known and that k divides N. You must describe the map and reduce phases of the round, specifying the intermediate and output key-value pairs.

Solution. The algorithm is the following.

Round 1

• Map phase: map each pair $(\mathrm{ID}_x, (x, f))$ with f = 0 into the intermediate pair $(\mathrm{ID}_x \bmod N/k, (x, f))$, and each pair $(\mathrm{ID}_x, (x, f))$ with f = 1 into the N/k pairs (i, (x, f)), with $0 \le i < N/k$. Let P_i be the set of intermediate pairs (i, (x, f)) with f = 0 and S_i the set of intermediate pairs (i, (x, f)) with f = 1. (Note that S_i is a replica of the set of centers S.)

• Reduce phase: For each key $i \in [0, N/k)$ independently, gather the set P_i and S_i . For each $(i, (x, 0)) \in P_i$ determine the pair $(i, (y, 1)) \in S_i$ such that y is the closest center to x, breaking ties arbitrarily, and output the pair (x, y) (i.e., x is assigned to the cluster with center y. Also, if i = 0, for each $(i, (y, 1)) \in S_i$, output the pair (y, y) (i.e., y is assigned to the cluster centered at itself).

The map phase requires constant local space, while in the reduce phase, each reducer gathers a subset P_i of size k and a replica S_i of the set of k centers. Therefore, $M_L = O(k)$. As for the aggregate space, each of the k centers is replicated N/k times, while other points are not replicated. Altogether, we have $M_A = O(N)$.

Exercise. Let P be a set of points in a metric space (M,d), and let $T \subseteq P$. For any k < |T|, show that $\Phi^{\text{opt}}_{\text{kcenter}}(T,k) \leq 2\Phi^{\text{opt}}_{\text{kcenter}}(P,k)$, where $\Phi^{\text{opt}}_{\text{kcenter}}(X,k)$ is the minimum value of $\Phi_{\text{kcenter}}(\mathcal{C})$ over all possible k-clusterings \mathcal{C} of a pointset X.

Solution. The solution is essentially embodied in the proof of the approximation bound for the MR-Farthest-First Traversal algorithm (Slides 47-49 on clustering, Part 1), where the application of the Farthest-First Traversal algorithm on subsets of a pointset P was analyzed. Let $S = \{c_1, c_2, \ldots, c_k\}$ be the k centers returned by the Farthest-First Traversal algorithm when applied on T, and let q be the point of T with maximum distance from S. Clearly, each point in T is at distance $\leq d(q, S)$ from S, therefore the clustering C of T induced by the centers in S is such that $\Phi_{\text{kcenter}}(C) = d(q, S)$. This also implies that $\Phi_{\text{kcenter}}^{\text{opt}}(T, k) \leq \Phi_{\text{kcenter}}(C) = d(q, S)$. Now, as claimed in the analysis of the MR-Farthest-First Traversal algorithm, we have that the set $\{c_1, c_2, \ldots, c_k, q\}$ comprises k+1 points of T, hence of P, whose pairwise distances are all $\geq d(q, S)$. Since at least two of these points must belong to the same cluster in the optimal k-clustering of P, we have that $d(q, S) \leq 2\Phi_{\text{kcenter}}^{\text{opt}}(P, k)$. By combining the various inequalities we obtain

$$\Phi_{\text{kcenter}}^{\text{opt}}(T, k) \le d(q, S) \le 2\Phi_{\text{kcenter}}^{\text{opt}}(P, k).$$

Observation. The previous exercise raises the natural question whether the relation proved there is tight, in the sense that there exists a pointset P, a subset $T \subseteq P$, and a value k such that $\Phi_{\text{kcenter}}^{\text{opt}}(T,k) = 2\Phi_{\text{kcenter}}^{\text{opt}}(P,k)$. Indeed, this is the case. For given k, consider the following set P of k+2 points in \Re (i.e., on the line):

$$P = \{-1, 0, 1, x, 2x, \dots, (k-1)x\},\$$

where x is very large (e.g., x=1000). It is easy to see that an optimal k-clustering of P uses, as centers, the points ix, with $0 \le i \le k-1$, and that $\Phi_{\text{kcenter}}^{\text{opt}}(P,k) = 1$. Let

$$T = \{-1, 1, x, 2x, \dots, (k-1)x\} \subseteq P.$$

It is easy to see that an optimal k-clustering of T uses, as centers, the points ix, with $1 \le i \le k-1$, plus either 1 or -1, and that $\Phi_{\text{kcenter}}^{\text{opt}}(T,k)=2$.

Exercise. Let P be a set of N points in a metric space (M, d), and let $T \subseteq P$ be a coreset of |T| > k points such that for each $x \in P$, we have $d(x, T) < \Phi_{\text{kcenter}}^{\text{opt}}(P, k)$, where $\Phi_{\text{kcenter}}^{\text{opt}}(P, k)$ is the minimum value of $\Phi_{\text{kcenter}}(C)$ over all possible k-clusterings C of P.

- 1. Devise a MapReduce algorithm which receives in input P and T and computes a good solution for the k-center clustering problem on P, using local space $M_L = O(|T|)$ and aggregate space $M_A = O(N)$. You need not describe in detail map and reduce phases and key-value pairs. Also, you can assume that for a set of k centers $S \subseteq P$, the primitive Partition(P, S) can be implemented in MapReduce in 1 round, using local space proportional to k and linear aggregate space.
- 2. Determine the approximation ratio achieved by your algorithm.

Solution.

- 1. The algorithm is the following:
 - Round 1: gather T into one reducer and compute a set $S \subseteq T$ of k centers using the Farthest-First Traversal algorithm on T.
 - Round 2: Execute Partition (P, S) to compute the final clustering.

The first round requires local space proportional to |T| and linear aggregate space, while the primitive Partition, invoked in the second round, can be executed with local space proportional to k and linear aggregate space. Hence, since |T| > k, the algorithm needs $M_L = O(|T|)$ and $M_A = O(N)$.

2. Let q be the point of T with maximum distance from the centers of S (denote this distance by d(q, S)). By reasoning as in the proof of the approximation bound for the MR-Farthest-First Traversal algorithm (Slides 47-49 of the slides on Clustering Part 1), we can show that $d(q, S) \leq 2\Phi^{\rm opt}_{\rm kcenter}(P, k)$. Consider a point $x \in P$. From the hypothesis on T we know that there is a point $y \in T$ such that $d(x, y) \leq \Phi^{\rm opt}_{\rm kcenter}(P, k)$. Also, by the properties of S we known that there is a center $c \in S$ such that $d(y, c) \leq d(q, S)$. These considerations yield that

$$\begin{array}{ll} d(x,c) & \leq & d(x,y) + d(y,c) \\ & \leq & \Phi_{\mathrm{kcenter}}^{\mathrm{opt}}(P,k) + d(q,S) \\ & \leq & \Phi_{\mathrm{kcenter}}^{\mathrm{opt}}(P,k) + 2\Phi_{\mathrm{kcenter}}^{\mathrm{opt}}(P,k) \\ & = & 3\Phi_{\mathrm{kcenter}}^{\mathrm{opt}}(P,k). \end{array}$$

Therefore, the clustering \mathcal{C} returned by the algorithm is such that $\Phi_{\text{kcenter}}(\mathcal{C}) \leq 3\Phi_{\text{kcenter}}^{\text{opt}}(P,k)$, that is, the approximation ratio is 3.

Exercise. Show how to implement one iteration of Lloyd's algorithm in MapReduce using a constant number of rounds, local space $M_L = O\left(\sqrt{N}\right)$ and aggregate space $M_A = O\left(N\right)$, when $k = O\left(\sqrt{N}\right)$. Assume that at the beginning of the iteration a set S of k centers and a current estimate Φ of the objective function are available. The iteration must compute the partition of P around S, the new set S' of k centers, and it must update Φ , unless it is the last iteration. You need not describe in detail map and reduce phases and key-value pairs.

Solution. The implementation is the following. Let $S = \{c_1, c_2, \dots, c_k\}$.

• Round 1: Partition P arbitrarily into \sqrt{N} subsets P_i , with $0 \le i < \sqrt{N}$, of size \sqrt{N} each. For each $0 \le i < \sqrt{N}$ independently, gather P_i and a copy of S and compute

$$P_{ij} = \{x \in P_i : d(x, S) = d(x, c_j)\}$$

$$X_{ij} = \sum_{x \in P_{ij}} x$$

$$\operatorname{num}_{ij} = |X_{ij}|.$$

• Round 2: for each $1 \leq j \leq k$ independently, gather the values X_{ij} and num_{ij} , with $0 \leq i < \sqrt{N}$, and compute

$$c'_{j} = \frac{\sum_{i=0}^{\sqrt{N}-1} X_{ij}}{\sum_{i=0}^{\sqrt{N}-1} \text{num}_{ij}}.$$

Let $S' = \{c'_1, c'_2, \dots, c'_k\}.$

• Round 3: for each $0 \le i < \sqrt{N}$ independently, gather P_i and a copy of S' and compute

$$\phi_i = \sum_{x \in P_i} d^2(x, S').$$

• Round 4: gather all ϕ_i 's into one reducer and compute

$$\Phi' = \sum_{i=0}^{\sqrt{N}-1} \phi_i.$$

If $\Phi' < \Phi$ then update Φ with the new value Φ' .

Each round requires local space $O\left(k+\sqrt{N}\right)=O\left(\sqrt{N}\right)$. As for the aggregate space, the \sqrt{N} copies of S and S' take, altogether, space $O\left(N\right)$, and all other data also require space $O\left(N\right)$.

Exercise. Consider a set P of N points in \Re^D . Let $\Phi_{\text{kmeans}}^{\text{opt}}(k)$ be the minimum value of $\Phi_{\text{kmeans}}(\mathcal{C})$ over all possible k-clusterings \mathcal{C} of P, and let $\mathcal{C}_{\text{alg}} = \text{Partition}(S, P)$ be the k-clustering of P induced by the set S of centers returned by the k-means++.

1. Using Markov's inequality determine a value c(k) > 0 such that

$$\Pr\left(\Phi_{\text{kmeans}}(\mathcal{C}_{\text{alg}}) \le c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)\right) \ge 1/2.$$

Recall that for a real-valued nonnegative random variable X with expectation E[X] and a value a > 0, the Markov's inequality states that

$$\Pr(X \ge a) \le \frac{E[X]}{a}.$$

2. Show that by running $\log_2 N$ independent instances of k-means++ and by taking the best clustering $\mathcal{C}_{\text{best}}$ found among all repetitions, we have that

$$\Pr\left(\Phi_{\text{kmeans}}(\mathcal{C}_{\text{best}}) \le c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)\right) \ge 1 - 1/N.$$

Solution.

1. Because of the random choices made by k-means++, we have that $\Phi_{\text{kmeans}}(\mathcal{C}_{\text{alg}})$ is a real-valued nonnegative random variable, whose expectation is

$$E[\Phi_{\text{kmeans}}(\mathcal{C}_{\text{alg}})] \leq 8(\ln k + 2) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k).$$

Let us define $c(k) = 16(\ln k + 2)$. By Markov's inequality we have that

$$\Pr(\Phi_{\text{kmeans}}(\mathcal{C}_{\text{alg}}) \ge c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)) \le \frac{E[\Phi_{\text{kmeans}}(\mathcal{C}_{\text{alg}})]}{c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)} \le \frac{1}{2}.$$

This implies that $\Pr(\Phi_{\text{kmeans}}(\mathcal{C}_{\text{alg}}) \leq c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)) \geq 1/2$.

2. Let C_i be the k-clustering obtained in the i-th instance of k-means++, for $1 \leq i \leq \log_2 N$. Since the $\log_2 N$ instances are independent, we have that

$$\Pr(\Phi_{\text{kmeans}}(\mathcal{C}_{\text{best}}) \ge c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)) = \prod_{i=1}^{\log_2 N} \Pr(\Phi_{\text{kmeans}}(\mathcal{C}_i) \ge c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k))$$

$$\le \frac{1}{2^{\log_2 N}} = \frac{1}{N}.$$

Therefore, $\Pr(\Phi_{\text{kmeans}}(\mathcal{C}_{\text{best}}) \leq c(k) \cdot \Phi_{\text{kmeans}}^{\text{opt}}(k)) \geq 1 - 1/N$.

Exercise. Show that the PAM algorithm always terminates.

Solution. Refer to the pseudocode of the algorithm (see Slide 22 of the slides on Clustering Part 2). Let C_i be the clustering stored by variable C at the end of the i-th iteration of the while-loop, where C_0 is the initial clustering. Note that each C_i is obtained by invoking the primitive Partition on some set of centers, hence it is uniquely determined by the centers. Also, by construction, the values $\Phi_{\text{kmedian}}(C_i)$ are strictly decreasing with i, except for the last value. Therefore, the sets of centers that yield the C_i 's must be all distinct except for the last one. This immediately implies that the number of iterations cannot be more than the number of subsets of k points, which is $\binom{N}{k}$, where N is the number of input points. \square

Exercise. Let P be a dataset of N points in some metric space (M,d), let X be a random sample of t points from P, and let Y be a random sample of t points from M, for some $t = O\left(\sqrt{N}\right)$. Show that the Hopkins statistic H(P) can be efficiently computed in MapReduce, assuming that P, X and Y are given as input. You need not describe in detail map and reduce phases and key-value pairs, but may assume that initially each point comes with a distinct key in [0, N-1].

Solution. The algorithm is the following.

- Round 1. Do the following:
 - Partition P into \sqrt{N} subsets P_j , with $0 \le j < \sqrt{N}$, of \sqrt{N} points each
 - Create \sqrt{N} copies of both X and Y.
 - For every $0 \leq j < \sqrt{N}$ independently, gather P_j , a copy of X, a copy of Y, and compute $w_x(j) = \min_{z \in P_j, z \neq x} d(x, z)$, for each $x \in X$, and $u_y(j) = \min_{z \in P_j, z \neq y} d(y, z)$, for each $y \in Y$.
- Round 2. For each $x \in X$ (resp., $y \in Y$), independently, gather all $w_x(j)$'s (resp., $u_y(j)$'s) and compute $w_x = \min_{0 \le j \le \sqrt{N}} w_x(j)$ (resp., $u_y = \min_{0 \le j \le \sqrt{N}} u_y(j)$)
- Round 3. Gather all values w_x , with $x \in X$, and all values u_y , with $y \in Y$ and compute

$$H(P) = \frac{\sum_{y \in Y} u_y}{\sum_{y \in Y} u_y + \sum_{x \in X} w_x}.$$

Each round requires local space $O\left(\sqrt{N}+t\right)=O\left(\sqrt{N}\right)$. As for the aggregate space, the \sqrt{N} copies of X and Y take, altogether, space $O\left(t\sqrt{N}\right)=O\left(N\right)$, and all other data also require space $O\left(N\right)$.

Exercise. Let P be a set of N points in a metric space (M,d), and let $\mathcal{C} = (C_1, C_2, \ldots, C_k; c_1, c_2, \ldots, c_k)$ be a k-clustering of P. Design and analyze an efficient MapReduce algorithm that for each cluster cluster center $c \in \{c_1, \ldots, c_k\}$ determines the most distant point among those belonging to the cluster centered at c. (Assume that all distances between pairs of points are distinct.) Initially, each point $q \in P$ is represented by a pair (ID(q), (q, c(q))), where ID(q) is a distinct key in [0, N-1] and $c(q) \in \{c_1, \ldots, c_k\}$ is the center of the cluster of q. Specify map and reduce phases, and intermediate and output pairs of each round. To get full score, the algorithm must use o(N) local space and linear aggregate space.

Solution. The algorithm is the following:

Round 1

- Map phase: each pair $(\mathrm{ID}(q), (q, c(q)))$ is mapped into the intermediate pair (j, (q, c(q))), with $j = \mathrm{ID}(q) \bmod \sqrt{N}$.
- Reduce phase: For each $0 \le j < \sqrt{N}$ independently, gather the set S_j of intermediate pairs with key j and select, for each center c, the most distant point q such that $(j, (q, c(q) = c)) \in S_j$ (if any such pair exists). Represent each selected point q as a new pair (c(q), q), where c(q) is the key.

Observation: At the end of the round there will be at most \sqrt{N} pairs with the same key c.

Round 2

- Map phase: identity.
- Reduce phase: for each center c independently, gather all pairs (c, q) (where c = c(q)) produced in the previous round, and return the pair with the largest values of d(c, q).

Correctness immediately follows by the observation that for each center c, if the most distant point q from the center is represented by a pair $(j, (q, c(q) = c)) \in S_j$, such a pair will be surely be selected in the first round, hence q will be identified as the most distant point from c in the second round. Since each S_j has size $\Theta\left(\sqrt{N}\right)$ and, in the first round, at most \sqrt{N} points are selected for each cluster, the local space is $M_L = \Theta\left(\sqrt{N}\right)$. Also, since for each point a constant number of pairs are ever used, the aggregate space linear in N.