

Multidimensional Scaling (MDS) by HappyZ Mar. 30

- Given d_{ij} , the distances between pairs of N points, MDS can place these points in a low (e.g. 2-D) space such that the Euclidean distance between them is as close as possible (i.e. given \mathbf{D} , approximate \mathbf{X}).
- Squared Euclidean distance (for points r and s):

- $d_{rs}^2 = \|\mathbf{x}^r - \mathbf{x}^s\|_2^2 = \sum_{j=1}^d (x_j^r - x_j^s)^2 = b_{rr} + b_{ss} - 2b_{rs}$ where $b_{rs} = \sum_{j=1}^d x_j^r x_j^s$
 - Or $d_{rs}^2 = \|\mathbf{x}_r - \mathbf{x}_s\|_2^2 = (\mathbf{x}_r - \mathbf{x}_s)^T (\mathbf{x}_r - \mathbf{x}_s) = \mathbf{x}_r^T \mathbf{x}_r - \mathbf{x}_s^T \mathbf{x}_s - 2\mathbf{x}_r^T \mathbf{x}_s$

$$\mathbf{D} = \mathbf{b}\mathbf{e}^T + \mathbf{e}\mathbf{b}^T - 2\mathbf{X}\mathbf{X}^T \text{ where } \mathbf{b} \text{ is the diagonal elements in } \mathbf{B} = \mathbf{X}\mathbf{X}^T \text{ and } \mathbf{e} \text{ is } [1 \ \dots \ 1]^T$$

- Define
 - $\mathbf{d}_{..}^2 = \frac{1}{N^2} \sum_r \sum_s d_{rs}^2$ or $\mathbf{d}_{..} = \frac{1}{N^2} \mathbf{e}^T \mathbf{D} \mathbf{e}$
 - $d_{r.}^2 = \frac{1}{N} \sum_s d_{rs}^2$ or $\mathbf{d}_{r.} = \frac{1}{N} \mathbf{D} \mathbf{e}$
 - $d_{.s}^2 = \frac{1}{N} \sum_r d_{rs}^2$ or $\mathbf{d}_{.s} = \mathbf{d}_{r.}^T = \frac{1}{N} \mathbf{e}^T \mathbf{D}$ since $\mathbf{D} = \mathbf{D}^T$
- Then $b_{rs} = \frac{1}{2} (d_{r.}^2 + d_{.s}^2 - d_{..}^2 - d_{rs}^2)$
 - Or $\mathbf{B} = \frac{1}{2} (\mathbf{d}_{r.} \mathbf{e}^T + \mathbf{e} \mathbf{d}_{.s} - \mathbf{d}_{..} \mathbf{e} \mathbf{e}^T - \mathbf{D}) = \mathbf{X}\mathbf{X}^T$

Proof. Assume all data is centered and $\mathbf{X}^T \mathbf{e} = 0$. Then $\mathbf{e}^T \mathbf{D} \mathbf{e} = \mathbf{e}^T \mathbf{b} \mathbf{e}^T \mathbf{e} + \mathbf{e}^T \mathbf{e} \mathbf{b}^T \mathbf{e} - 2\mathbf{e}^T \mathbf{X}\mathbf{X}^T \mathbf{e} = 2\tau N$, where $\tau = \mathbf{e}^T \mathbf{b}$ is the sum of all square distances, and $\mathbf{e}^T \mathbf{e} = N$, which is the number of points. Then $\tau = \frac{1}{2N} \mathbf{e}^T \mathbf{D} \mathbf{e}$.

Since $\mathbf{D} \mathbf{e} = \mathbf{b} \mathbf{e}^T \mathbf{e} + \mathbf{e} \mathbf{b}^T \mathbf{e} = N \cdot \mathbf{b} + \tau \cdot \mathbf{e}$, we get $\mathbf{b} = \frac{1}{N} (\mathbf{D} \mathbf{e} - \tau \cdot \mathbf{e})$.

Then $\mathbf{D} = \frac{\mathbf{D} \mathbf{e}}{N} \mathbf{e}^T - \frac{\tau}{N} \mathbf{e}^T \mathbf{e} + \mathbf{e} \left(\frac{\mathbf{D} \mathbf{e}}{N} \right)^T - \frac{\tau}{N} \mathbf{e} \mathbf{e}^T - 2\mathbf{B} = \frac{\mathbf{D} \mathbf{e}}{N} \mathbf{e}^T + \mathbf{e} \left(\frac{\mathbf{D} \mathbf{e}}{N} \right)^T - \frac{\mathbf{e}^T \mathbf{D} \mathbf{e}}{N^2} \mathbf{e} \mathbf{e}^T - 2\mathbf{B}$.

So $\mathbf{B} = \frac{1}{2} \left(\left(\frac{\mathbf{D} \mathbf{e}}{N} \right) \mathbf{e}^T + \mathbf{e} \left(\frac{\mathbf{D} \mathbf{e}}{N} \right)^T - \frac{\mathbf{e}^T \mathbf{D} \mathbf{e}}{N^2} \mathbf{e} \mathbf{e}^T - \mathbf{D} \right) = \frac{1}{2} (\mathbf{d}_{r.} \mathbf{e}^T + \mathbf{e} \mathbf{d}_{.s} - \mathbf{d}_{..} \mathbf{e} \mathbf{e}^T - \mathbf{D})$.

- So we approximate $\mathbf{X} = \mathbf{C}\sqrt{\mathbf{\Lambda}}$, where \mathbf{C} is the matrix whose columns are the eigenvectors of \mathbf{B} and $\sqrt{\mathbf{\Lambda}}$ is a diagonal matrix with square roots of the eigenvalues on the diagonals.
 - In terms of eigenvalues of \mathbf{B} , we decide on the dimensionality $k < d$ (and $k < N$) as we did in PCA. So the approximation of \mathbf{X} satisfies $z_j^t = \sqrt{\lambda_j} c_j^t, j = 1, 2, \dots, k, t = 1, \dots, N$
- The eigenvalues of $\mathbf{X}\mathbf{X}^T$ are the same as those of $\mathbf{X}^T \mathbf{X}$.

Ex. Replica of Figure 6.6 In the book (*Istanbul and Athens are wrong in the book*).

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% HappyZ @ Mar. 30, 2014
clear all; close all; clc
% Initialization
loc = {'Lisbon', 'Madrid', 'Dublin', 'London', 'Paris', 'Zurich', 'Rome', 'Berlin', ...
       'Helsinki', 'Istanbul', 'Moscow', 'Athens'};
% Following data comes from Google Maps (in miles)
D = [0, 388.5, 1734.3, 1352.9, 1078, 1317.2, 1559.5, 1726.7, 2534, 2541.3, 2830.1,
     2388.4; ...
     388.5, 0, 1444, 1062.6, 787.7, 1029.9, 1214.5, 1436.4, 2243.7, 2196.3, 2539.8,
     2043.5; ...
     1734.3, 1444, 0, 363.4, 656.1, 996.7, 1513.5, 1050.9, 1844.3, 2233.5, 2154.3,
     2330.6; ...
     1352.9, 1062.6, 363.4, 0, 283.5, 624.1, 1141, 678.4, 1471.7, 1860.9, 1781.8, 1958.1; ...
     1078, 787.7, 656.1, 283.5, 0, 407.3, 886.1, 651, 1458.3, 1714.3, 1754.4, 1811.4; ...
     1317.2, 1029.9, 996.7, 624.1, 407.3, 0, 533, 525.5, 1504.9, 1366.8, 1628.9, 1464; ...
     1559.5, 1214.5, 1513.5, 1141, 886.1, 533, 0, 936.6, 1773.8, 1085.5, 1897.8, 837.5; ...
     1726.7, 1436.4, 1050.9, 678.4, 651, 525.5, 936.6, 0, 1002.1, 1364.6, 1126.1, 1461.8; ...
     2534, 2243.7, 1844.3, 1471.7, 1458.3, 1504.9, 1773.8, 1002.1, 0, 2021.9, 687.7,
     2119.1; ...
     2541.3, 2196.3, 2233.5, 1860.9, 1714.3, 1366.8, 1085.5, 1364.6, 2021.9, 0, 1332.7,
     680.4; ...
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2830.1, 2539.8, 2154.3, 1781.8, 1754.4, 1628.9, 1897.8, 1126.1, 687.7, 1332.7, 0,
1852; ...
2388.4, 2043.5, 2330.6, 1958.1, 1811.4, 1464, 837.5, 1461.8, 2119.1, 680.4, 1852, 0];
N = length(D);
e = ones(N, 1);
% define d's based on eq. 6.26
d_dotdot = 1/N^2*(e'*D*e);
d_rdot = 1/N*(D*e);
d_dots = 1/N*(e'*D); % since D = D'
B = 1/2*(d_rdot*e' + e*d_dots - d_dotdot*e*e' - D);
[V, EigVals] = eig(B);
[o, i] = sort(diag(EigVals), 'descend');
V = V(:, i); EigVals = EigVals(i, i);
C = V(:, 1:2);
Diag = sqrt([EigVals(1,1); EigVals(2,2)]);
X = [Diag(1)*C(:,1), Diag(2)*C(:,2)];
scatter(-X(:,1), -X(:,2), 'k. ');
for i = 1:N
    if (i == 2) text(-X(i, 1) + 0.5, -X(i, 2) + 0.5, loc{i}); % fix overlapping
    else text(-X(i, 1) + 0.5, -X(i, 2) - 0.8, loc{i}); end
end
title({'Replica of Figure 6.6 in book "Introduction to Machine Learning";
'Distance data comes from Google Maps, by HappyZ @ Mar. 30'});
xlabel('miles'); ylabel('miles');
xlim([-25, 30]); ylim([-25, 25]);

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