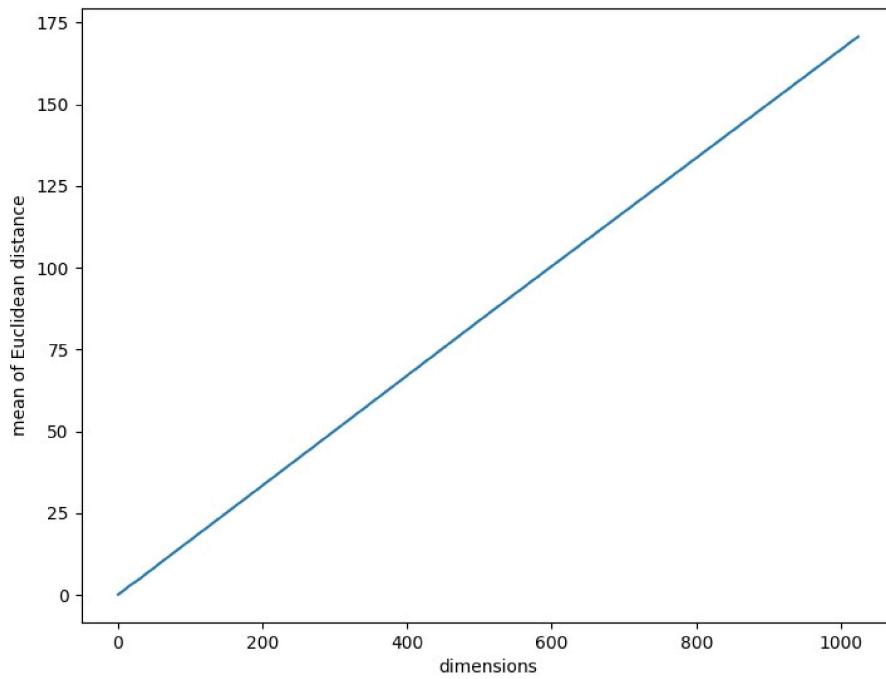
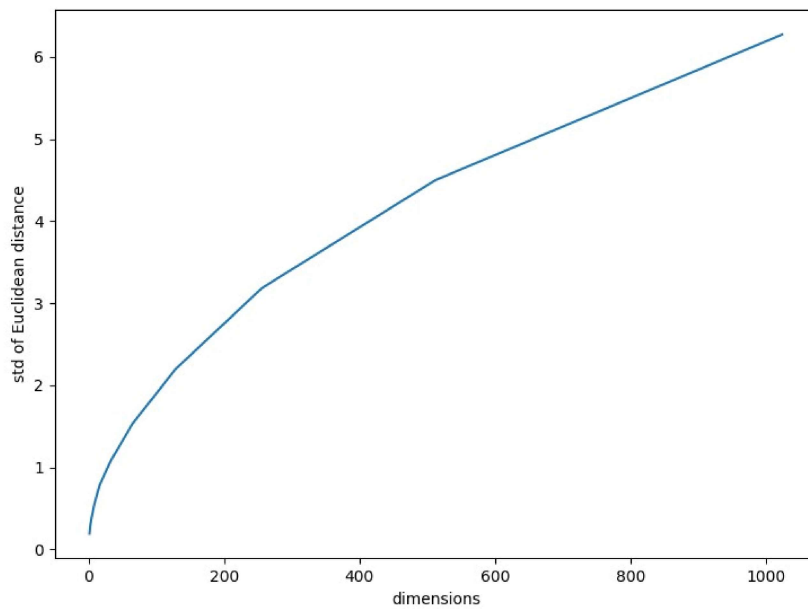


Q1 output for mean-dimension :



output for std-dimension :



Q1 b) assume all z_i are independent of each other;

$$\text{Thus } E(R) = E\left(\sum_{i=1}^d z_i\right) = \sum_{i=1}^d E(z_i)$$

$$= \sum_{i=1}^d \frac{1}{6} = \frac{d}{6}$$

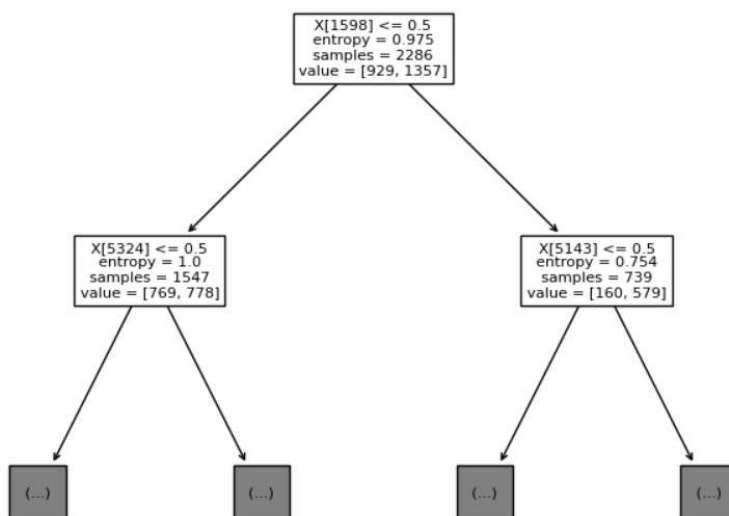
$$V(R) = V\left(\sum_{i=1}^d z_i\right) = \sum_{i=1}^d V(z_i) = \sum_{i=1}^d \frac{7}{180} = \frac{7d}{180}$$

Q2 b)

```
model: entropy; depth: 5; accuracy: 0.70816
model: gini; depth: 5; accuracy: 0.71224
model: entropy; depth: 12; accuracy: 0.72245
model: gini; depth: 12; accuracy: 0.76531
model: entropy; depth: 20; accuracy: 0.76531
model: gini; depth: 20; accuracy: 0.77143
model: entropy; depth: 30; accuracy: 0.78163
model: gini; depth: 30; accuracy: 0.76939
model: entropy; depth: 45; accuracy: 0.76735
model: gini; depth: 45; accuracy: 0.76122
```

← classifier of entropy
with depth 30 yields
highest accuracy;

C>



Qzd

keyword 1598: 0.05614365126920684

keyword 5143: 0.05278618037184435

keyword 5324: 0.04315750865439716

$$\begin{aligned}
 Q3 a) \quad \frac{\partial J_{reg}}{\partial w_j} &= \frac{\partial}{\partial w_j} \left(\frac{1}{2N} \sum_{i=1}^N \left(\sum_{j'=1}^D w_{j'} x_{ij'} + b - t_i \right)^2 + \frac{1}{2} \sum_{j'=1}^D \beta_{j'} w_{j'}^2 \right) \\
 &= \frac{1}{N} \sum_{i=1}^N \left(\sum_{j'=1}^D w_{j'} x_{ij'} + b - t_i \right) \cdot \frac{\partial}{\partial w_j} \left(\sum_{j'=1}^D w_{j'} x_{ij'} + b - t_i \right) \\
 &\quad + \frac{\partial}{\partial w_j} \frac{1}{2} \beta_1 w_1^2 + \dots \frac{\partial}{\partial w_j} \frac{1}{2} w_j^2 \beta_j + \dots \frac{\partial}{\partial w_D} \frac{1}{2} w_D^2 \beta_D \\
 &= \frac{1}{N} \sum_{i=1}^N \left(\sum_{j'=1}^D w_{j'} x_{ij'} + b - t_i \right) x_{ij} + \beta_j w_j
 \end{aligned}$$

$$\text{thus } w_j \leftarrow w_j - \frac{\alpha}{N} \sum_{i=1}^N (y_i - t_i) x_{ij} - \beta_j w_j$$

$$\begin{aligned}
 \frac{\partial J_{reg}}{\partial b} &= \frac{\partial}{\partial b} \left(\frac{1}{2N} \sum_{i=1}^N \left(\sum_{j'=1}^D w_{j'} x_{ij'} + b - t_i \right)^2 + \frac{1}{2} \sum_{j'=1}^D \beta_{j'} w_{j'}^2 \right) \\
 &= \frac{1}{N} \sum_{i=1}^N (y_i - t_i) \cdot \frac{\partial}{\partial b} \left(\sum_{j'=1}^D w_{j'} x_{ij'} + b - t_i \right) \\
 &= \frac{1}{N} \sum_{i=1}^N (y_i - t_i) \cdot \left(\sum_{j'=1}^D 0 + 1 - 0 \right) = \frac{1}{N} \sum_{i=1}^N (y_i - t_i) \\
 b &\leftarrow b - \frac{\alpha}{N} \left(\sum_{i=1}^N (y_i - t_i) \right)
 \end{aligned}$$

Q3 b)

$$\begin{aligned}
 \frac{\partial J_{reg}}{\partial w_j} &= \frac{1}{2N} \left[\sum_{i=1}^N \left(\sum_{j'=1}^d w_{j'} x_{ij'} - t_i \right)^2 \right]' + \frac{1}{2} \left[\sum_{j'=1}^D (\beta_{j'} w_{j'}^2) \right]' \\
 &= \frac{1}{N} \sum_{i=1}^N \left(\sum_{j'=1}^d w_{j'} x_{ij'} - t_i \right) x_{ij} + \beta_j w_j \\
 &= \frac{1}{N} \left[\sum_{i=1}^N (w_1 x_{i1} x_{ij} + \dots w_j x_{ij}^2 + \dots w_d x_{id} x_{ij} - t_i x_{ij}) \right] + \beta_j w_j
 \end{aligned}$$

$$= \frac{1}{N} \left[\sum_{j'=1}^D w_{j'} \left(\sum_{i=1}^N x_{ij'} x_{ij} \right) - \sum_{i=1}^N t_i x_{ij} \right] + \beta_j w_j$$

$$\text{when } j'=j \quad A_{jj} = \frac{1}{N} \sum_{i=1}^N x_{ij} x_{ij} + \beta_j \quad C_j = \frac{1}{N} \sum_{i=1}^N t_i x_{ij}$$

$$j' \neq j \quad A_{jj'} = \frac{1}{N} \sum_{i=1}^N x_{ij'} x_{ij}$$

Q3C > let $\vec{\beta} = [\beta_1, \dots, \beta_D]$;

by treating each entry of matrix A as the dot product of \vec{x} s, (data vectors),

$$A = \frac{1}{N} \left[\begin{array}{ccc} \sum_{i=1}^N x_{i1} x_{i1} & \dots & \sum_{i=1}^N x_{iD} x_{i1} \\ \vdots & \ddots & \vdots \\ \sum_{i=1}^N x_{i1} x_{iD} & \dots & \sum_{i=1}^N x_{iD} x_{iD} \end{array} \right] + \vec{\beta} \cdot N \cdot I$$

Since $X = \begin{bmatrix} \vec{x}_1 \\ \vdots \\ \vec{x}_n \end{bmatrix}_{N \times D}$ then the dot product matrix is formed

by : $X^T X$; since X^T has dimension $D \times N$, thus

$X^T X$ has dimension $D \times D \Rightarrow$ can multiply with \vec{w} ($1 \times D$)

Then $A = \frac{1}{N} (X^T X + \vec{\beta} N I)$;

$$C = \begin{bmatrix} C_1 \\ \vdots \\ C_D \end{bmatrix} = \frac{1}{N} \begin{bmatrix} \sum_{i=1}^N x_{i1} \cdot t_i \\ \vdots \\ \sum_{i=1}^N x_{iD} \cdot t_i \end{bmatrix} = \frac{1}{N} (X^T \cdot \vec{t})$$

since X^T has dimension $D \times N$,
which is multiplicable
with \vec{t} having dimension $N \times 1$

$$\text{Thus } A w = C \Rightarrow w = A^{-1} C = (X^T X + \vec{\beta} N I)^{-1} \cdot (X^T \cdot \vec{t})$$