CSCI-SHU 360 Machine Learning Solution to homework 1

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1 Simpson's Paradox

1.1

We use A to indicate that I win, and B to indicate that my friend wins. We use M_i to indicate the player plays on the ith machine. We have

$$P(A|M_1) = \frac{2}{5}, P(A|M_2) = \frac{21}{104}$$
$$P(B|M_1) = \frac{3}{10}, P(B|M_2) = \frac{1}{6}$$

Thus, on both machine 1 and machine 2, I am more likely to win.

1.2

$$P(A) = \frac{40 + 210}{40 + 60 + 210 + 830} = \frac{25}{114}$$
$$P(B) = \frac{30 + 14}{30 + 70 + 14 + 70} = \frac{11}{46}$$

Thus, my friend is more likely to win.

1.3

$$P(A) = P(A|M_1)P(M_1) + P(A|M_2)P(M_2)$$

$$P(B) = P(B|M_1)P(M_1) + P(B|M_2)P(M_2)$$

Thus, when the $P(M_i)$ increses, the total winning probability of player will get closer to the winning rate of machine i.

Thus, as I played much more rows on machine 2, and the overall winning rate on machine 2 is smaller than machin 1, my winning rate will get closer to the smaller winning rate(which is the winning rate of machine 2), and my friend's winning rate will be closer to the higher winning rate(which is the winning rate of machine 1), and that lead to the result that my winning rate is high on both machine, but the overall winning rate is lower than my friend.

2 Matrix as Operations

2.1

$$a_1 = (1,0), b_1 = (2,0)$$

 $a_2 = (0,1), b_2 = (3,2)$

Suppose $W = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix}$ We have

$$b_{1} = Wa_{1} = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} W_{11} \\ W_{21} \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$
$$b_{2} = Wa_{2} = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} W_{12} \\ W_{22} \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \end{bmatrix}$$

Thus, we have

$$W = \begin{bmatrix} 2 & 3 \\ 0 & 2 \end{bmatrix}$$

2.2

From $\tan(\alpha) = 2$, we have $\sin(\alpha) = \frac{2\sqrt{5}}{5}$ and $\cos(\alpha) = \frac{\sqrt{5}}{5}(\text{Suppose }\alpha \in (0,\pi))$ Moreover, we have the formula of the rotation matrix:

$$R = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$$

When θ is the clockwise rotation angle. Thus,

$$V = \begin{bmatrix} \frac{\sqrt{5}}{5} & \frac{2\sqrt{5}}{5} \\ -\frac{2\sqrt{5}}{5} & \frac{\sqrt{5}}{5} \end{bmatrix}$$

As Σ scales the x-axis by a factor of 4 in two-dimensional space, the matrix is:

$$\Sigma = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix}$$

By using the same approach, we can get matrix U. $\tan(\beta) = \frac{1}{2}, \sin(\beta) = \frac{\sqrt{5}}{5}, \cos(\beta) = \frac{2\sqrt{5}}{5},$ And

$$U = \begin{bmatrix} \frac{2\sqrt{5}}{5} & -\frac{\sqrt{5}}{5} \\ \frac{\sqrt{5}}{5} & \frac{2\sqrt{5}}{5} \end{bmatrix}$$

Multiplying three matrices together, we have:

$$\begin{split} U\Sigma V &= \begin{bmatrix} \frac{2\sqrt{5}}{5} & -\frac{\sqrt{5}}{5} \\ \frac{\sqrt{5}}{5} & \frac{2\sqrt{5}}{5} \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{5}}{5} & \frac{2\sqrt{5}}{5} \\ -\frac{2\sqrt{5}}{5} & \frac{\sqrt{5}}{5} \end{bmatrix} \\ &= \begin{bmatrix} \frac{2\sqrt{5}}{5} & -\frac{\sqrt{5}}{5} \\ \frac{\sqrt{5}}{5} & \frac{2\sqrt{5}}{5} \end{bmatrix} \begin{bmatrix} \frac{4\sqrt{5}}{5} & \frac{8\sqrt{5}}{5} \\ \frac{5}{5} & \frac{\sqrt{5}}{5} \end{bmatrix} \\ &= \begin{bmatrix} 2 & 3 \\ 0 & 2 \end{bmatrix} \\ &= W \end{split}$$

Thus, we have

$$U\Sigma V=W$$

2.3

We have

$$W = \begin{bmatrix} 2 & 3 \\ 0 & 2 \end{bmatrix}, W^T = \begin{bmatrix} 2 & 0 \\ 3 & 2 \end{bmatrix}$$

Thus

$$W^T W = \begin{bmatrix} 2 & 0 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 2 & 3 \\ 0 & 2 \end{bmatrix}$$
$$= \begin{bmatrix} 4 & 6 \\ 6 & 13 \end{bmatrix}$$

$$det(W^TW - \lambda I) = det \begin{pmatrix} 4 - \lambda & 6 \\ 6 & 13 - \lambda \end{pmatrix}$$
$$= (13 - \lambda)(4 - \lambda) - 36$$
$$= (\lambda - 16)(\lambda - 1)$$

Thus, the eigenvalues and eigenvectors of W^TW are:

$$\begin{cases} \lambda_1 = 1, u_1 = \begin{bmatrix} -2\\1 \end{bmatrix} \\ \lambda_2 = 16, u_2 = \begin{bmatrix} 1\\2 \end{bmatrix} \end{cases}$$

By applying the linear transformation W, the unit circle is rotated clockwise by α degrees, and then scales along x-axis by 4, finally, rotated counter-clockwise by β degrees. And this transformation results in a ellipse.

2.4

The determinant of W is det(W) = 4. As in the previous transformation, we scaled along x-axis by 4, the semi-major axis is 4, and the semi-minor axis is 1. Thus, the area of the ellipse is $1 \times 4 \times \pi = 4\pi$ As the origin unit circle has an area of π , we came up with the hypothesis that the determinant shows the change of the area of a transformed shape. Using a sentence to explain that det(AB) = det(A)det(B). Linear transformation AB means to perform first A and B, and this means the total effect of the change of area will first be the effect of A, then multiplys the effect of B, which in total is det(A)det(B).

3 Some Practices

3.1

As X is a discrete random variable, X^3 is also a discrete random variable. As $Var(X^3) = \mathbb{E}[X^6] - (\mathbb{E}[X^3])^2$ and $Var(X^3) \ge 0$, we can prove that:

$$(\mathbb{E}[X^3])^2 < \mathbb{E}[X^6]$$

3.2

$$(\mathbb{E}[X^3])^2 = (\sum_{i=1}^n p_i X_i^3)^2$$
$$\mathbb{E}[X^6] = \sum_{i=1}^n p_i X_i^6$$

We expand the square of expectation, which means:

$$(\mathbb{E}[X^3])^2 = (\sum_{i=1}^n p_i X_i^3)^2 = \sum_{i=1}^n \sum_{j=1}^n p_i p_j X_i^3 X_j^3$$

We know that $2ab \le a^2 + b^2$, and by letting $a = X_i^3$ and $b = X_j^3$, we can conclude that $X_i^3 X_j^3 \le \frac{X_i^6 + X_j^6}{2}$. Thus, we can prove that:

$$(\mathbb{E}[X^3])^2 = \sum_{i=1}^n \sum_{j=1}^n p_i p_j X_i^3 X_j^3$$

$$\leq \sum_{i=1}^n \sum_{j=1}^n p_i p_j \frac{X_i^6 + X_j^6}{2}$$

$$= \sum_{i=1}^n \sum_{j=1}^n p_i p_j \frac{X_i^6}{2} + \sum_{i=1}^n \sum_{j=1}^n p_i p_j \frac{X_j^6}{2}$$

As for i, we have $\sum_{i=1}^{n} p_i = 1$ (Which is also true for j), we can prove that:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} p_{i} p_{j} \frac{X_{i}^{6}}{2} + \sum_{i=1}^{n} \sum_{j=1}^{n} p_{i} p_{j} \frac{X_{j}^{6}}{2} = \sum_{i=1}^{n} p_{i} \frac{X_{i}^{6}}{2} + \sum_{j=1}^{n} p_{j} \frac{X_{j}^{6}}{2}$$
$$= \sum_{i=1}^{n} p_{i} X_{i}^{6}$$
$$= \mathbb{E}[X^{6}]$$

Thus, we can prove:

$$(\mathbb{E}[X^3])^2 \le \mathbb{E}[X^6]$$

3.3

For PSD matrices A we have $x^TAx \ge 0$ for every x. And for $0 \le \lambda \le 1$ we have $\lambda \ge 0, 1 - \lambda \ge 0$. As $x^TAx \ge 0, x^TBx \ge 0$ we can conclude that $x^T\lambda Ax \ge 0, x^T(1-\lambda)Bx \ge 0$ Thus we can prove:

$$x^{T}\lambda Ax + x^{T}(1-\lambda)Bx \ge 0$$
$$x^{T}(\lambda Ax + (1-\lambda)B)x \ge 0$$

Thus we can prove that the matrix $\lambda Ax + (1 - \lambda)B$ is also PSD for $0 \le \lambda \le 1$