

Deep Learning Homework Assignment 1

Solutions and Grading Policy by Keyi Liu

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Problem 1 (10 points)

Given 3 Random Variables(RVs), and their joint probability mass $P(X, Y, Z) = P(X)P(Y)P(Z|X, Y)$.

(a) Show that RV X and Y are marginally independent. You can either show that $P(X, Y) = P(X)P(Y)$,

$$\begin{aligned} P(X, Y) &= \sum_Z P(X, Y, Z) = \sum_Z P(X)P(Y)P(Z|X, Y) \\ &= P(X)P(Y) \sum_Z P(Z|X, Y) = P(X)P(Y) \end{aligned} \quad (1)$$

as desired. Or, you can also show that $P(X|Y) = P(X)$, of course $P(Y|X) = P(Y)$ is equivalent,

$$\begin{aligned} P(X|Y) &= \frac{P(X, Y)}{P(Y)} = \frac{\sum_Z P(X, Y, Z)}{P(Y)} = \frac{\sum_Z P(X)P(Y)P(Z|X, Y)}{P(Y)} \\ &= \frac{P(X)P(Y) \sum_Z P(Z|X, Y)}{P(Y)} = P(X) \end{aligned} \quad (2)$$

as desired.

Gradings 5 points subtotal, correctly applying the sum rule (**3 points**), properly simplified and get the final equation another (**2 points**).

(b) Show that X and Y are conditionally dependent given Z . By definition, you can show that $P(X, Y|Z) \neq P(X|Z)P(Y|Z)$,

$$\begin{aligned} P(X, Y|Z) &= \frac{P(X, Y, Z)}{P(Z)} = \frac{P(Z)P(Y|Z)P(X|Y, Z)}{P(Z)} \\ &= P(X|Y, Z)P(Y|Z) \end{aligned} \quad (3)$$

thus $P(X, Y|Z) \neq P(X|Z)P(Y|Z)$ as desired.

Gradings 5 points subtotal, correctly apply the chain rule (**3 points**), obtain the final conclusion correctly (**2 points**). Note that the way of applying the chain rule is not unique, you will get points for other ways of applying it.

Problem 2 (10 points)

The given event (rolling a die) follows a multinomial distribution. Denote the RV which is the number of landing on different values $i (i = 1, \dots, 6)$ as X_i , and θ_i the associated probability of each value i , then the Probability Mass Function (PMF) of this multinomial distribution is given as,

$$\begin{aligned} f(x_1, \dots, x_6; n, \theta_1, \dots, \theta_6) &= Pr(X_1 = x_1, X_2 = x_2, \dots, X_6 = x_6) \\ &= \frac{n!}{x_1! \dots x_6!} \theta_1^{x_1} \dots \theta_6^{x_6} \end{aligned} \quad (4)$$

where $\sum_{i=1}^6 x_i = n$.

Here, we have $n = 100$, plug in the x'_i 's and θ'_i 's and we will get the probability,

$$\begin{aligned} &P(X_1 = 20, X_2 = 15, X_3 = 10, X_4 = 5, X_5 = 20, X_6 = 30) \\ &= \frac{100!}{20! \times 15! \times 10! \times 5! \times 20! \times 30!} \times 0.25^{20} \times 0.3^{15} \times 0.1^{10} \times 0.1^5 \times 0.15^{20} \times 0.1^{30} = 4.53 \times 10^{-14} \end{aligned} \quad (5)$$

Gradings Identifying that this is a multinomial distribution (**3 points**), correctly show the probability mass function you will get another (**5 points**), and calculate the final probability correctly (**2 points**).

Problem 3 (10 points)

Given the joint probability distribution of $P(X, Y, Z)$, you are asked to show that any pair of RVs are marginally independent of each other. Take RV X and Y as an example, by definition, you will need to show that $P(X, Y) = P(X)P(Y)$ for each configuration of (X, Y) (It is also correct if you can show that $P(X|Y) = P(X)$).

You can start from the marginal,

$$P(X = 0) = \sum_{Y, Z} P(X = 0, Y, Z) = 1/12 + 1/6 + 1/6 + 1/12 = 1/2 \quad (6)$$

$$P(X = 1) = 1 - P(X = 0) = 1/2$$

$$P(Y = 0) = \sum_{X, Z} P(X, Y = 0, Z) = 1/12 + 1/6 + 1/6 + 1/12 = 1/2 \quad (7)$$

$$P(Y = 1) = 1 - P(Y = 0) = 1/2$$

Then, compute the joint probability for X and Y ,

$$\begin{aligned} P(X = 1, Y = 1) &= \sum_Z P(X = 1, Y = 1, Z) = 1/12 + 1/6 = 1/4 \\ P(X = 0, Y = 0) &= \sum_Z P(X = 0, Y = 0, Z) = 1/12 + 1/6 = 1/4 \\ P(X = 1, Y = 0) &= \sum_Z P(X = 1, Y = 0, Z) = 1/12 + 1/6 = 1/4 \\ P(X = 0, Y = 1) &= \sum_Z P(X = 0, Y = 1, Z) = 1/12 + 1/6 = 1/4 \end{aligned} \quad (8)$$

We can then check that for each configuration of (X, Y) , we have $P(X, Y) = P(X)P(Y)$, thus it follows that X and Y are marginally independent of each other. You can repeat similar process for other two pair of RVs, and get the same conclusion.

Gradings You will get **9 points** if you correctly show one of the three pairs of RVs' independency, i.e. **(3 points)** for each of $P(X)$, $P(Y)$, and $P(X, Y)$ in my sample solution. If you get all three pairs correctly, you will get the total 10 points.

Problem 4 (10 points)

The covariance matrix Σ for RV \mathbf{X} is a symmetric and positive semi-definite matrix with all its entries real values. Thus the Eigen Decomposition exists, and is given as,

$$\Sigma = \mathbf{Q}\Lambda\mathbf{Q}^{-1} \quad (9)$$

where \mathbf{Q} is a $N \times N$ orthonormal matrix, with its columns the eigenvectors of Σ , and Λ a diagonal matrix with eigenvalues of Σ on its main diagonal.

The Singular Value Decomposition is given as,

$$\Sigma = \mathbf{U}\mathbf{D}\mathbf{V}^T \quad (10)$$

and for symmetric matrix, it is reduced to

$$\Sigma = \mathbf{U}\mathbf{D}\mathbf{U}^T \quad (11)$$

where \mathbf{U} is also a orthonormal matrix containing singular vectors in its columns, and \mathbf{D} a diagonal matrix with the singular value of Σ along its main diagonal.

From Eigen Decomposition we have,

$$\begin{aligned} \Sigma^T \Sigma &= (\mathbf{Q}\Lambda\mathbf{Q}^{-1})^T \mathbf{Q}\Lambda\mathbf{Q}^{-1} \\ &= \mathbf{Q}^{-T} \Lambda^T \mathbf{Q}^T \mathbf{Q}\Lambda\mathbf{Q}^{-1} \\ &= \mathbf{Q}\Lambda^T \Lambda \mathbf{Q}^T \end{aligned} \quad (12)$$

Note that, \mathbf{Q} is orthonormal, so we have $\mathbf{Q}^T = \mathbf{Q}^{-1}$.

From Singular Value Decomposition we have,

$$\begin{aligned} \Sigma^T \Sigma &= (\mathbf{U}\mathbf{D}\mathbf{V}^T)^T \mathbf{U}\mathbf{D}\mathbf{V}^T \\ &= \mathbf{U}\mathbf{D}^T \mathbf{D} \mathbf{U}^T \end{aligned} \quad (13)$$

It is obvious that both Λ , and \mathbf{D} contain the square root of the eigenvalues of matrix $\Sigma^T \Sigma$, thus $\Lambda = \mathbf{D}$, and it follows that $\mathbf{U} = \mathbf{Q}$, namely, the Eigen Decomposition is equivalent to SVD.

Gradings Correctly give the formula of both Eigen Decomposition and SVD worth **(4 points)**, compare the resulting matrices and give proper analysis **(6 points)**, specifically, claim that in $\mathbf{U}\mathbf{D}\mathbf{V}^T$, $\mathbf{U} = \mathbf{V}$, Λ and \mathbf{D} are diagonal matrices containing eigenvalues, and that $\mathbf{Q} = \mathbf{U}$, each **(2 points)**.

Problem 5 (10 points)

Given a scalar functional $f(\mathbf{X})$, with the coefficient matrices A, b, C, d not a function of \mathbf{X} , let

$$g(\mathbf{X}) = (A\mathbf{X} + b)^T(C\mathbf{X} + d) + \lambda\mathbf{X}^T\mathbf{X} \quad (14)$$

Thus we shall calculate the partial derivative w.r.t. \mathbf{X} , i.e.

$$\begin{aligned} \frac{\partial f(\mathbf{X})}{\partial \mathbf{X}} &= \frac{\partial \log(g(\mathbf{X}))}{\partial g(\mathbf{X})} \times \frac{\partial g(\mathbf{X})}{\partial \mathbf{X}} \\ &= \frac{1}{g(\mathbf{X})} \times \frac{\partial g(\mathbf{X})}{\partial \mathbf{X}} \end{aligned} \quad (15)$$

where

$$\begin{aligned} \frac{\partial g(\mathbf{X})}{\partial \mathbf{X}} &= \frac{\partial [(A\mathbf{X} + b)^T(C\mathbf{X} + d)]}{\partial \mathbf{X}} + \lambda \frac{\partial \mathbf{X}^T\mathbf{X}}{\partial \mathbf{X}} \\ &= \frac{\partial (A\mathbf{X} + b)}{\partial \mathbf{X}}(C\mathbf{X} + d) + \frac{\partial (C\mathbf{X} + d)}{\partial \mathbf{X}}(A\mathbf{X} + b) + 2\lambda \frac{\partial \mathbf{X}}{\partial \mathbf{X}}\mathbf{X} \\ &= A^T(C\mathbf{X} + d) + C^T(A\mathbf{X} + b) + 2\lambda\mathbf{X} \end{aligned} \quad (16)$$

Thus combine Equation (14), (15), and (16), we have,

$$\frac{\partial f(\mathbf{X})}{\partial \mathbf{X}} = \frac{A^T(C\mathbf{X} + d) + C^T(A\mathbf{X} + b) + 2\lambda\mathbf{X}}{(A\mathbf{X} + b)^T(C\mathbf{X} + d) + \lambda\mathbf{X}^T\mathbf{X}} \quad (17)$$

Note that, the dimension of the result is the same as $\mathbf{X}^{N \times 1}$.

The rules that are used here,

(1)

$$\frac{\partial U\mathbf{X}}{\partial \mathbf{X}} = U^T$$

(2)

$$\frac{\partial U^TV}{\partial \mathbf{X}} = \frac{\partial U}{\partial \mathbf{X}}V + \frac{\partial V}{\partial \mathbf{X}}U$$

Gradings Correctly applying the chain rule and get the correct derivative for $\log(\cdot)$ (**5 points**), correctly applying the above rules and calculate the remaining parts of the derivatives (**5 points**).