

# ECE-GY 6143 Machine Learning HW 03

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## 1 Problem 1

### 1.1 a

sales data

### 1.2 b

consider  $i^{th}$  trial as  $\mathbf{x}^T = x_1, x_2, \dots, x_n$ , mapping the numerical value and frequency to  $[0, 1]$  and feed into  $\mathbf{x}^T$ , and let prediction  $y = \mathbf{x}^T \beta$

### 1.3 c

both mapping to  $[0, 1]$

### 1.4 d

mapping numeric score to  $[0, 1]$

mapping binary score to  $\{0, 1\}$

no review neutral to the mean of all other scores  $\{x\}$

### 1.5 e

proportion of *good* in all reviews

## 2 Problem 3

### 2.1 a

$$\Phi_1(\mathbf{x}) = x_1 e^{-x_1 - x_2}, \beta_1 = a_1$$

$$\Phi_2(\mathbf{x}) = x_2 e^{-x_1 - x_2}, \beta_2 = a_2$$

## 2.2 b

$$\begin{aligned}\Phi_1(\mathbf{x}) &= u(x-1), \beta_1 = a_1 \\ \Phi_2(\mathbf{x}) &= u(x-1)x, \beta_2 = a_2 \\ \Phi_3(\mathbf{x}) &= u(1-x), \beta_3 = a_3 \\ \Phi_4(\mathbf{x}) &= u(1-x)x, \beta_4 = a_4\end{aligned}$$

## 2.3 c

$$\begin{aligned}\Phi_1(\mathbf{x}) &= e^{-x_2}, \beta_1 = e^{a_2} \\ \Phi_2(\mathbf{x}) &= x_1 e^{-x_2}, \beta_2 = a_1 e^{a_2}\end{aligned}$$

## 3 Problem 4

### 3.1 a

$$\beta.shape = [M + N + 1,]$$

### 3.2 b

$$\begin{bmatrix} 0 & \dots & 0 & x_0 & \dots & 0 \\ y_0 & \dots & 0 & x_1 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ y_{k-1} & \dots & y_{k-M} & x_k & \dots & x_{k-N} \end{bmatrix}$$

$$A.shape = [T, M + N + 1]$$

### 3.3 c

considering the dot product  $A^T * A$  can be blocked into four parts, for the product, **only difference between row and column index would impact result**:

$$B = \begin{bmatrix} A^T[:, M, :] * A[:, : M] & A^T[:, M, :] * A[:, M : ] \\ A^T[M :, :] * A[:, : M] & A^T[M :, :] * A[:, M : ] \end{bmatrix}$$

$$\begin{aligned}A^T[:, M, :] * A[:, : M] : B[i, j] &= R_{yy}(|i - j|) \\ A^T[:, M, :] * A[:, M : ] : B[i, j] &= R_{xy}(i - j) \\ A^T[M :, :] * A[:, : M] : B[i, j] &= R_{xy}(j - i) \\ A^T[M :, :] * A[:, M : ] : B[i, j] &= R_{xx}(|i - j|)\end{aligned}$$

For same reason,  $C = A^T y$  could be simplified as:

$$\begin{aligned}C[:, M] : C[i, j] &= R_{yy}(|i - j|) \\ C[M :] : C[i, j] &= R_{xy}((i - j))\end{aligned}$$

## 4 Problem 6

### 4.1 a

```
x[:,2] *= x[:,1]
yhat = np.dot(x, beta)
```

### 4.2 b

```
A = np.dot(x.reshape([x.shape[0],1]), beta.reshape([1,beta.shape[0]]))
yhat = np.dot(-np.exp(A), alpha)
```

### 4.3 c

```
dim = np.ones(x.shape[1])
Sig_X = np.dot(x**2, dim).reshape(x.shape[0],1)
Sig_Y = np.dot(y**2, dim).reshape(1,y.shape[0])
dist = Sig_X + Sig_Y - 2*np.dot(x,y)
```