A Feature Selection Study for Medical Image deep learning

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Outline

- Deep Feature Selection study
- Thyroid Associated Ophthalmopathy Research
- Industry-University Collaboration Project

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \leftrightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \widetilde{U}C$$

where $\widetilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is $\mathrm{diag}\{s\}$ and s=$(s_1, \ldots\, s_p)$ has nonnegative entries.

Deep Feature Selection study

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where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is diag$\{s\}$ and s=$(s_1, \ldots s_p)$ has nonnegative entries.

- $X = \begin{vmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ -\frac{1}{\sqrt{2}} \end{vmatrix}, \Sigma = |1|, \Sigma^{-1} = |1|$
- $\tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C = \begin{vmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ -\frac{1}{\sqrt{2}} \end{vmatrix}(|1| - |1|\mathrm{S}) + \tilde{U}C$

Deep Feature Selection study

- $G = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix}$ is positive semi-definite matrix,

  IFF, $2\Sigma - S \geq 0$ and $2S - S\Sigma^{-1}S \geq 0$

Equi-correlated knockoffs:

$$s_j = 2\lambda_{min}(\Sigma) \wedge 1, \text{ where } \tilde{X}_j^T X_j = 1 - s_j, \mathrm{diag}\{s\} \leq 2X^T X$$

=> minimize $|(\tilde{X}_j^T \quad X_j)|$

$$s_1 = 2\lambda_{min}(\Sigma) \wedge 1 = 2 \wedge 1 = 1$$

$$S = |1|$$

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \quad \leftrightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is $\mathrm{diag}\{s\}$ and s=$(s_1, \ldots\ s_p)$ has nonnegative entries.

- $U^T X = 0$ and $U^T U = I$

  - Deterministic U

    1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\,R$

    2: $U \leftarrow Q_0$

Deep Feature Selection study

$\widetilde{U}$ is orthonormal to the column space of X, $U^T X = 0$ and $U^T U = I$

1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\ R$

$$\left[X\ 0_{n\times p}\right] = \begin{vmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 0 \\ -\frac{1}{\sqrt{2}} & 0 \end{vmatrix}$$

- QR decomposition:

  A=QR where A is a $m \times n$ complex matrix, Q is a $m \times n$ unitary matrix and R is a $\mathrm{n} \times n$ upper triangular matrix.

  If A is real matrix, then, Q is orthogonal matrix.

  If A has n linearly independent columns, then the first n columns of Q form an orthonormal basis for the column space of A.

Deep Feature Selection study

- QR decomposition: A=QR

  If A has n linearly independent columns, then the first n columns of Q form an orthonormal basis for the column space of A.

- Gram-Schmidt process:

  Given linearly independent set of vectors $\{v_1, \ldots, v_k\}$ in an inner product space V (i.e. $\mathbb{R}^n$), calculate orthonormal basis $\{e_1, \ldots, e_k\}$

$$u_1 = v_1$$
$$u_2 = v_2 - proj_{u_1}(v_2)$$
$$u_3 = v_3 - proj_{u_1}(v_3) - proj_{u_2}(v_3)$$
$$\vdots$$
$$u_k = v_k - \sum_{j=1}^{k-1} proj_{u_j}(v_k)\, , e_k = \frac{u_k}{||u_k||}$$

Deep Feature Selection study

$\tilde{U}$ is orthonormal to the column space of X, $U^T X = 0$ and $U^T U = I$

1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\ R$

$$[Q_x^T Q_0^T]\left[X\ 0_{n\times p}\right] = R$$

$$\begin{bmatrix} Q_x^T\ X & Q_x^T\ 0 \\ Q_0^T\ X & Q_0^T\ 0 \end{bmatrix} = \begin{bmatrix} Q_x^T\ X & 0 \\ Q_0^T\ X & 0 \end{bmatrix} = R$$

∵ If $A = QR$ is QR decomposition of A, $Q^T Q = I$ and R is an upper triangular matrix

2: $U \leftarrow Q_0$

Deep Feature Selection study

$\widetilde{U}$ is orthonormal to the column space of X, $U^T X = 0$ and $U^T U = I$

1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\ R$

$$\left[X\ 0_{n\times p}\right] = \begin{vmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 0 \\ -\frac{1}{\sqrt{2}} & 0 \end{vmatrix} = \begin{vmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{vmatrix} R$$

- Thin decomposition phase:

$$u_1 = v_1 = \left(\frac{1}{\sqrt{2}}, 0, -\frac{1}{\sqrt{2}}\right) \therefore q_{11} = \frac{1}{\sqrt{2}}\ q_{21} = 0,\ q_{31} = -\frac{1}{\sqrt{2}}$$

$$u_2 = v_2 - proj_{u_1}(v_2) = (0, 0, 0) \therefore q_{12} = 0\ q_{22} = 0,\ q_{32} = 0$$

- Full decomposition phase:

$$q_{11} \times q_{13} + q_{21} \times q_{23} + q_{31} \times q_{33} = 0, \quad q_{12} \times q_{13} + q_{22} \times q_{23} + q_{32} \times q_{33} = 0$$

Deep Feature Selection study

$\widetilde{U}$ is orthonormal to the column space of X, $U^T X = 0$ and $U^T U = I$

1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\ R$

$$\left[X\ 0_{n\times p}\right] = \begin{vmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 0 \\ -\frac{1}{\sqrt{2}} & 0 \end{vmatrix} = \begin{vmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{vmatrix} R$$

- Full decomposition phase:

$$\frac{1}{\sqrt{2}} \times q_{13} + 0 \times q_{23} - \frac{1}{\sqrt{2}} \times q_{33} = 0,\ \ 0 \times q_{13} + 0 \times q_{23} + 0 \times q_{33} = 0 \quad \therefore q_{13} = q_{33}$$

$$q_{13} = q_{33} = t,\ \sqrt{t^2 + t^2 + q_{23}^2} = 1$$

$$=> t = \frac{1}{\sqrt{2}},\ \therefore q_{13} = \frac{1}{\sqrt{2}},\ q_{23} = 0,\ q_{33} = \frac{1}{\sqrt{2}}$$

Deep Feature Selection study

$\widetilde{U}$ is orthonormal to the column space of X, $U^TX = 0$ and $U^TU = I$

1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\ R$

$$\left[X\ 0_{n\times p}\right] = \begin{vmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 0 \\ -\frac{1}{\sqrt{2}} & 0 \end{vmatrix} = \begin{vmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{vmatrix} R$$

- Reassign q_{12} , q_{22} and q_{32} :

$$\frac{1}{\sqrt{2}} \times q_{12} + 0 \times q_{22} - \frac{1}{\sqrt{2}} \times q_{32} = 0 \text{ -> } q_{12} - q_{32} = 0$$

$$\frac{1}{\sqrt{2}} \times q_{12} + 0 \times q_{22} + \frac{1}{\sqrt{2}} \times q_{32} = 0 \text{ -> } q_{12} + q_{32} = 0$$

$$\therefore q_{12} = q_{32} = 0,\ q_{22} = 1 \text{ for } U^TU = I$$

Deep Feature Selection study

$\widetilde{U}$ is orthonormal to the column space of X, $U^T X = 0$ and $U^T U = I$

1: Perform QR decomposition $\left[X\ 0_{n\times p}\right] = [Q_x\ Q_0]\ R$

$$\left[X\ 0_{n\times p}\right] = \begin{vmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 0 \\ -\frac{1}{\sqrt{2}} & 0 \end{vmatrix} = \begin{vmatrix} \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \end{vmatrix} R$$

2: $U \leftarrow Q_0$

Q_0 can be $\begin{vmatrix} 0 & \frac{1}{\sqrt{2}} \\ 1 & 0 \\ 0 & \frac{1}{\sqrt{2}} \end{vmatrix}$ by Gram–Schmidt process. $\therefore U = \begin{vmatrix} 0 & \frac{1}{\sqrt{2}} \\ 1 & 0 \\ 0 & \frac{1}{\sqrt{2}} \end{vmatrix}$

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \quad \rightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is diag$\{s\}$ and s=$(s_1, \ldots s_p)$ has nonnegative entries.

$\tilde{X}^{\mathrm{T}}X = \Sigma - S$ and $\tilde{X}^{\mathrm{T}}\tilde{X} = \Sigma$

$$\tilde{X} = \mathrm{A} + \mathrm{X}$$

$$A^T X = (\tilde{X} - \mathrm{X})^T X = \Sigma - S - \Sigma = -\mathrm{S} \qquad \Rightarrow A^T X = -\mathrm{S}$$

$$\Sigma = \tilde{X}^{\mathrm{T}}\tilde{X} = (A + X)^T(A + X) = A^T A + \Sigma - 2S \qquad \Rightarrow A^T A = 2S$$

Choose an orthonormal matrix $U \in R^{n\times(n-p)}$, then A can be expressed as

$$A = XB + UC \text{ with } B \in R^{p\times p},\ C \in R^{(n-p)\times p}$$

$$(n \times p) = (n \times p) \times (p \times p) + (n \times (n-p)) \times ((n-p) \times p)$$

$$U^T X = X^T U = 0 \text{ and } U^T U = I$$

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \quad \leftrightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is diag$\{s\}$ and s=$(s_1, \ldots s_p)$ has nonnegative entries.

- $\tilde{X} = \mathrm{A} + \mathrm{X}$
- $A^T X = -\mathrm{S}$
- $A^T A = 2S$
- $A = XB + UC$
- $U^T X = X^T U = 0$ and $U^T U = I$

$$-\mathrm{S} = A^T X = X^T A = X^T(XB + UC) = \Sigma B + 0 \quad \Rightarrow \quad B = -\Sigma^{-1}S$$

$$2S = A^T A = (B^T X^T + C^T U^T)(XB + UC) = B^T \Sigma B + C^T C$$

$$= S\Sigma^{-1}S + C^T C \qquad \Rightarrow C^T C = 2S - S\Sigma^{-1}S$$

$$\tilde{X} = \mathrm{A} + \mathrm{X} = (XB + UC) + X = X - X\Sigma^{-1}S + UC = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \quad \leftrightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is diag$\{s\}$ and s=$(s_1, \dots s_p)$ has nonnegative entries.

- $\Sigma^{-1} = |1|$, $S = |1|$
- $2S - S\,\Sigma^{-1}S = 2 \times |1| - |1| \times |1| \times |1| = |1| = \mathrm{C}^{\mathrm{T}}C$
- $\mathrm{C}^{\mathrm{T}}C = |1|$, $C \in R^{(n-p)\times p}$ ($A = LL^T$ by Cholesky decomposition where L is a lower-triangular matrix)
- C=$\begin{vmatrix} C_1 \\ 0 \end{vmatrix} \in R^{(n-p)\times p}$, $C_1 \in R^{p\times p}$ and $C_1^T C_1$=$\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S$
- $C_1 = |1|$, $C = \begin{vmatrix} 1 \\ 0 \end{vmatrix}$

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \quad \leftrightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is $\mathrm{diag}\{s\}$ and s=($s_1, \ldots s_p$) has nonnegative entries.

$$\Sigma^{-1} = |1|, S = |1|,\ U = \begin{vmatrix} 0 & \frac{1}{\sqrt{2}} \\ 1 & 0 \\ 0 & \frac{1}{\sqrt{2}} \end{vmatrix},\ C = \begin{vmatrix} 1 \\ 0 \end{vmatrix}$$

$$\tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C = \begin{vmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ -\frac{1}{\sqrt{2}} \end{vmatrix}(|1| - |1| \times |1|) + \begin{vmatrix} 0 & \frac{1}{\sqrt{2}} \\ 1 & 0 \\ 0 & \frac{1}{\sqrt{2}} \end{vmatrix} \times \begin{vmatrix} 1 \\ 0 \end{vmatrix} = \begin{vmatrix} 0 \\ 1 \\ 0 \end{vmatrix}, X = \begin{vmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ -\frac{1}{\sqrt{2}} \end{vmatrix},$$

Deep Feature Selection study

- $X = \begin{vmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{2} \\ 0 & \frac{1}{2} \\ -\frac{1}{\sqrt{2}} & 0 \\ 0 & \frac{1}{2} \\ 0 & -\frac{1}{2} \end{vmatrix}, \Sigma = \begin{vmatrix} 1 & -\frac{1}{2\sqrt{2}} \\ -\frac{1}{2\sqrt{2}} & 1 \end{vmatrix}, \Sigma^{-1} = \frac{8}{7}\begin{vmatrix} 1 & \frac{1}{2\sqrt{2}} \\ \frac{1}{2\sqrt{2}} & 1 \end{vmatrix},$

$S = \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix}$ by Equi-correlated knockoffs (minimum eigen value is 0.65),

$U = \begin{vmatrix} 0.64 & 0.09 & -0.09 \\ 0.38 & -0.53 & 0.53 \\ 0.64 & 0.09 & -0.09 \\ 0.13 & 0.81 & 0.19 \\ -0.13 & 0.19 & 0.81 \end{vmatrix}$ by QR decomposition, C= $\begin{vmatrix} 0.93 & -0.44 \\ 0 & 0.82 \\ 0 & 0 \end{vmatrix}$

Deep Feature Selection study

$$\tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

$$= \begin{vmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{2} \\ 0 & \frac{1}{2} \\ -\frac{1}{\sqrt{2}} & 0 \\ 0 & \frac{1}{2} \\ 0 & -\frac{1}{2} \end{vmatrix} \times \left(I - \frac{8}{7} \begin{vmatrix} 1 & \frac{1}{2\sqrt{2}} \\ \frac{1}{2\sqrt{2}} & 1 \end{vmatrix} \times \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} \right) + \begin{vmatrix} 0.64 & 0.09 & -0.09 \\ 0.38 & -0.53 & 0.53 \\ 0.64 & 0.09 & -0.09 \\ 0.13 & 0.81 & 0.19 \\ -0.13 & 0.19 & 0.81 \end{vmatrix} \times \begin{vmatrix} 0.93 & -0.44 \\ 0 & 0.82 \\ 0 & 0 \end{vmatrix}$$

$$= \begin{vmatrix} 0.69 & -0.42 \\ 0.15 & -0.67 \\ 0.69 & 0.08 \\ -0.08 & 0.54 \\ 0.08 & 0.28 \end{vmatrix}$$

Deep Feature Selection study

$$X = \begin{vmatrix} 0.71 & -0.5 \\ 0 & 0.5 \\ 0.71 & 0 \\ 0 & 0.5 \\ 0 & -0.5 \end{vmatrix} \Rightarrow X^T X = \begin{vmatrix} 1 & -\frac{1}{2\sqrt{2}} \\ -\frac{1}{2\sqrt{2}} & 1 \end{vmatrix} \approx \begin{vmatrix} 1 & -0.35 \\ -0.35 & 1 \end{vmatrix}$$

$$\tilde{X} = \begin{vmatrix} 0.69 & -0.42 \\ 0.15 & -0.67 \\ 0.69 & 0.08 \\ -0.08 & 0.54 \\ 0.08 & 0.28 \end{vmatrix} \Rightarrow \tilde{X}^T \tilde{X} \approx \begin{vmatrix} 1 & -0.35 \\ -0.35 & 1 \end{vmatrix}$$

$$\Rightarrow X^T X \approx \tilde{X}^T \tilde{X}$$

$$\tilde{X}^T X \approx \tilde{X}^T X \approx \begin{vmatrix} 0 & -0.35 \\ -0.35 & 0 \end{vmatrix} \approx \Sigma - S \approx \begin{vmatrix} 1 & -0.35 \\ -0.35 & 1 \end{vmatrix} - \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix}$$

Deep Feature Selection study

$$[X\tilde{X}]^T[X\tilde{X}] = \begin{vmatrix} \Sigma & \Sigma - S \\ \Sigma - S & \Sigma \end{vmatrix} \quad \leftrightarrow \quad \tilde{X} = X(\mathrm{I} - \Sigma^{-1}\mathrm{S}) + \tilde{U}C$$

where $\tilde{U}$ is orthonormal to the column space of X, $C \in R^{(n-p)\times p}$ satisfies $\mathrm{C}^{\mathrm{T}}C = 2S - S\,\Sigma^{-1}S \geq 0$, S is $\mathrm{diag}\{s\}$ and s=$(s_1, \ldots\, s_p)$ has nonnegative entries.

1) The original set and the knockoff set have the same covariance matrix.
2) Swapping an original and corresponding knockoff does not change covariance with other features.
3) The correlation between original and corresponding knockoff is defined as low as possible.

Deep Feature Selection study

- Next Step is to calculate feature statistics W.

If the W_j is large positive value, the f_j is more likely to be selected.

"If an original variable cannot be distinguished from its knockoff version in the regression model, it is identified as having a null effect."

- In KnockoffGAN (Jordon et al., 2018),

$$L_D = \sum_{S\in\{0,1\}^d} \mathbb{E}_{\ X\sim P_x}[\mathbb{E}_{\ \tilde{X}\sim P_{\tilde{X}}}[S - \log(D(\left(X,\tilde{X}\right)_{swap(S)})) + (1-S)\cdot\log(1-D(\left(X,\tilde{X}\right)_{swap(S)}))]]$$

- Generating Knockoffs methods -> imitating originals by a specific approach
- In my opinion, by imitating correlation structure, control the null features with a lot of collinearity and by knockoffGAN, control the redundant features and Features that are not unique.

Thyroid Associated Ophthalmopathy Research

- 완료 현황: 각각 1323명 환자 (기존에는 1267 환자)

유형	눈 (L)	눈 (R)	시신경 (L)	시신경 (R)	내직근 (L)	내직근 (R)	외직근 (L)	외직근 (R)	상직근 (L)	상직근 (R)	하직근 (L)	하직근 (R)	상안검 (L)	상안검 (R)	지방 (L)	지방 (R)	눈물주머니 (L)	눈물주머니 (R)	안와 (L)	안와 (R)	평균
AX 1	0.85	0.81	0.42	0.47	0.64	0.63	0.73	0.66							0	0					0.52
AX 2	0.91	0.89	0.75	0.72	0.93	0.93	0.93	0.9							0	0					0.70
AX 3	0.96	0.96	0.95	0.94	0.95	0.96	0.94	0.95							0	0					0.76
AX 4	0.94	0.94	0.82	0.84	0.82	0.84	0.79	0.75							0	0					0.67
AX 5	0.81	0.81	0.36	0.37	0.34	0.36	0.32	0.38							0	0					0.38
AX 6																	0	0			0.00
CO 1	0.96	0.96																			0.96
CO 2			0.89	0.89	0.91	0.91	0.91	0.89	0.86	0.9	0.91	0.88									0.90
CO 3																			0	0	0.00
SA 1		0.96		0.92						0.96		0.93		0.96							0.95
SA 2	0.96		0.92						0.96		0.93		0.96								0.95
계																					0.67

0% 100%

Thyroid Associated Ophthalmopathy Research

- 향후 진행해야할 업무:
  - 사전 수동 업무
    (1) 새로 추가된 환자에 대해 슬라이스 선정 작업 (AX1~5, CO1~3, SA1~2)
    (2) 지방 (AX1~5), 눈물 주머니 (AX6), 안와 (CO3), 훈련셋 세그멘테이션 작업
    (3) 실패 케이스에 대해, 구조물이 육안으로 식별되지 않는 경우를 카운팅 (AX1, AX5 주요하게, 이루어질 수 있음)
    (4) 나머지 (훈련셋을 제외한) 눈물 주머니 슬라이스 (AX6) 선정 작업
    - 자동 업무: 남은 모든 이미지
  - 이어서, 자동 세그멘테이션이 어려운 이미지에 대한 세그멘테이션 및 검토
- 계획:
  6.1~6.7: (1), (2) 진행
  6.8~6.14: (3), (4) 진행
  6.15~6.24: 자동 업무 및 잔여 수동 세그멘테이션

Industry-University Collaboration Project

- 제출 실적
  - SW 제작 (산학 1), 국제학술대회 논문 1편 이상 게재 (산학 2), 국내 특허출원 1건 이상 (산학 2)
- 현재 진행 사항
  - SW 제작: 진행중
  - 특허 출원: 기존 논문 번역본 제작 중
  - 투고 저널 리스트업 완료

Industry-University Collaboration Project

컨퍼런스명	개최기간	데드라인
International Conference on Computer Science, Industrial Electronics(ICCSIE) 16th Aug 2021, Seoul,Korea (south)	08/16 (월별로 개최)	8/1
1138th International Conference on Management and Information Technology (ICMIT),Seoul, Korea (south)	09/18-19	9/3
International Conference on Computer science and Information Technology (ICCSIT), Seoul, Korea (south)	09/20	9/6
1178th International Conference on Artificial Intelligence and Soft Computing (ICAISC)	12/4-5	11/19
1182nd International Academic Conference on Development in Science and Technology (IACDST)	12/4-5	11/19
International Symposium on Advanced Intelligent Systems	12월 (예정)	세부정보 없음

References

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