

창원대학교 통계학과
전임교원 신규채용 공개강의

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January 10, 2024

1 Introduction

- History
- Research Overview

2 Research Areas

- 1. Variable selection
- 2. Non-Euclidean data analysis
- 3. Multi-source data integration

3 Future Research Plan

Introduction

History: Kipoong Kim

- I was born in Busan and lived there for 30 years
- Education
 - ▶ 2010–2016 B.S. in Statistics, Pusan National Univ.
 - ▶ 2016–2017 M.S. in Statistics, Pusan National Univ.
 - ▶ 2019–2022 Ph.D. in Statistics, Pusan National Univ.
- Teaching Experience
 - ▶ Spring & Fall 2021 Part-Time Lecturer
 - ★ (a) Statistical Programming Language, (b) Biostatistics,
 - ★ (c) Introduction to Statistics, (d) Mathematical Statistics
- Academic Positions
 - ▶ 2022–Present PostDoc. in Statistics, Seoul National Univ.

Research Overview

- Main interest is to develop new statistical methodologies to better understand the data produced in various fields.
- My research areas include:
 - ▶ Variable selection in high-dimensional data
 - ▶ Low-rank models for non-Euclidean data (e.g. compositional, spherical)
 - ▶ Multi-source data integration
- I am also interested in collaborating with researchers in other fields such as psychology, biology, plant genetics, and medicine.
- As a result, we have published a total of 16 papers in the last 5 years
 - ▶ Statistical methodology: 10 papers (SCIE=6)
 - ▶ Application: 6 papers (SCIE=5)

Research Overview

Variable selection

- Suppose that we observed p genetic variants (predictors) and q phenotypes (responses) from n individuals.
- Then, we can consider the following frameworks:
 - ▶ For $q = 1$, univariate linear regression

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon},$$

where $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)^T \in \mathbb{R}^p$ and $\mathbf{y} \in \mathbb{R}^n$.

- ▶ For $q > 1$, multivariate regression

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{E},$$

where $\mathbf{B} = \{\beta_{jk}\} \in \mathbb{R}^{p \times q}$ and $\mathbf{Y} \in \mathbb{R}^{n \times q}$.

Research Overview

Variable selection

- We aim to identify outcome-related variables (i.e., variable selection)

$$\{j : \beta_j \neq 0\} \text{ for } q = 1 \quad \text{or} \quad \{(j, k) : \beta_{jk} \neq 0\} \text{ for } q > 1$$

- To this end, many statistical methodologies have been developed over time, including the lasso and elastic-net.
- Here, we focused on **the external information** of genomic data to improve statistical power in variable selection.
 - ▶ Genetic network
 - ▶ Multi-response information

Research Overview

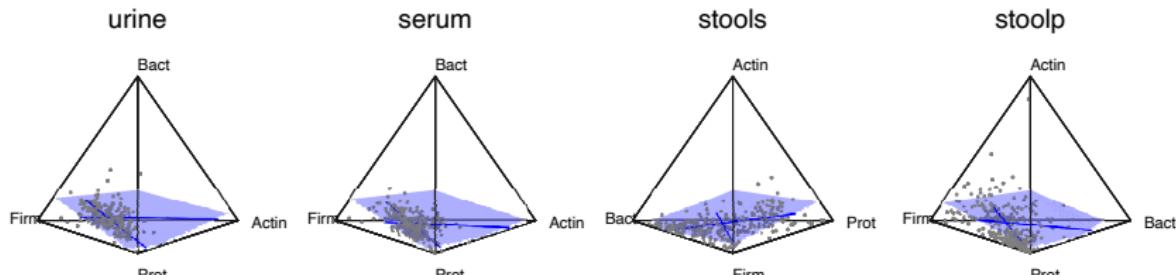
Incorporating external information in variable selection

- **Genetic network:** Kipoong Kim†, and Hokeun Sun (2019). “Incorporating Genetic networks into case-control association studies with high-dimensional DNA methylation data”. *BMC Bioinformatics*, 20, 510.
- **Multiple responses:** Kipoong Kim†, Taehwan Jun, Bokeun Ha, Shuang Wang and Hokeun Sun (2023). “New statistical selection method for pleiotropic variants associated with both quantitative and qualitative traits,” *BMC Bioinformatics*, 24, 381.
- For variable selection, an appropriate threshold π_{thr} is required
$$\hat{\mathcal{A}} = \{j : \Pi_j \geq \pi_{\text{thr}}\}.$$
- **Error control:** Kipoong Kim†, Jajoon Koo, and Hokeun Sun (2020). "An Empirical threshold of selection probability for analysis of high-dimensional correlated data," *Journal of Statistical Computation and Simulation*, 90(9), 1606–1617.

Research Overview

Low-rank models for non-Euclidean data

- **Microbiome compositional data:** Kipoong Kim†, Jaesung Park† and Sungkyu Jung (2024). “Principal Component Analysis for zero-inflated compositional data,” submitted to *Computational Statistics and Data Analysis*.
- We aim to find a **principal compositional subspace** and the corresponding principal scores minimizing the Euclidean projection error.



*Prot: Proteobacteria; Firm: Firmicutes; Actin: Actinobacteria; Bact: Bacteroidetes

- We also investigated **theoretical properties** of the principal compositional subspace including its existence and consistency.

Research Overview

Multi-source data integration

- Multi-source data can be thought of as a set of datasets produced from different multiple sources:

{ Gene expression, DNA methylation, RNA sequencing, ... }

- ▶ Each can be thought of as a design matrix, so we have

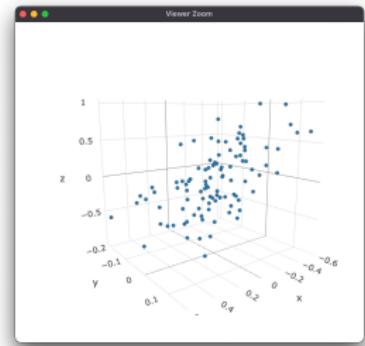
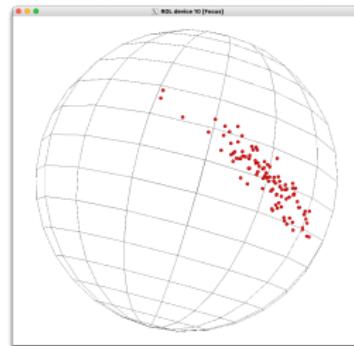
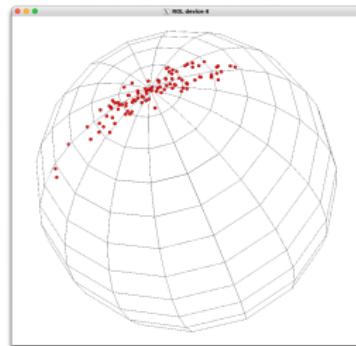
$$\mathbf{X} = [\mathbf{X}_{(1)}, \mathbf{X}_{(2)}, \mathbf{X}_{(3)}, \dots].$$

- The goal is to estimate the structural relationship between multi-source data \mathbf{X} and multiple responses \mathbf{Y} :
- **Multi-source data:** Kipoong Kim† and Sungkyu Jung (2024). “Integrative sparse reduced-rank regression via orthogonal rotation for analysis of high-dimensional multi-source data,” *Statistics and Computing*, 34, 2.

Research Overview

Non-Euclidean data integration

- Spherical data refers to data that is distributed on the surface of a hyper-sphere.
- Structural decomposition for multiple data sets (ongoing):



Key Statistical Methodology Papers

1. Variable selection: Incorporating genetic network

- Genomic data with a **group structure**: e.g. SNP, DNA-methylation.

$$\mathbf{X} = (\underbrace{\mathbf{X}_1, \dots, \mathbf{X}_{p_1}}_{\text{1st gene}} \mid \underbrace{\mathbf{X}_{p_1+1}, \dots, \mathbf{X}_{p_2}}_{\text{2nd gene}} \mid \cdots \mid \underbrace{\mathbf{X}_{p_{m-1}+1}, \dots, \mathbf{X}_{p_m}}_{\text{m-th gene}})$$

- ▶ Gene-level dimension reduction (2019)¹:

$$(\mathbf{X}_1, \dots, \mathbf{X}_{p_1} \mid \mathbf{X}_{p_1+1}, \dots, \mathbf{X}_{p_2} \mid \cdots \mid \mathbf{X}_{p_{m-1}+1}, \dots, \mathbf{X}_{p_m})$$
$$\downarrow \quad \quad \quad \downarrow \quad \quad \quad \downarrow$$
$$\tilde{\mathbf{X}}_1 \quad \quad \quad \tilde{\mathbf{X}}_2 \quad \quad \quad \tilde{\mathbf{X}}_m$$

- ▶ Group-wise penalties (2023+):

$$\arg \min_{\boldsymbol{\beta} \in \mathbb{R}^p} -\ell(\boldsymbol{\beta}) + \lambda_1 \sum_{k=1}^m \|\boldsymbol{\beta}_k\|_2 + \frac{\lambda_2}{2} \sum_{u \sim v} \left(\frac{\|\boldsymbol{\beta}_u\|_2}{\sqrt{d_u}} - \frac{\|\boldsymbol{\beta}_v\|_2}{\sqrt{d_v}} \right)^2.$$

¹K. Kim, H. Sun, *BMC bioinformatics* **20**, 1–15 (2019).

1. Variable selection: Multiple mixed-type responses

- In real application, many genetic studies include response variables with various data types such as continuous, ordinal and categorical:
 - e.g., cowpea dataset from Rural Development Administration:

Categories	Phenotypes		
Seed	Seed coat color	Seed coat pattern	Seed shape
	Seed coat gloss	100-seed weight	
Flowering	Flower color	Days for flowering	Days for ripening
Pod	Pod color Shattering	Pod curve Pod length	Seed density Seed numbers

■: categorical, ■: continuous

- Kim et al. (2023)² proposed a statistical method based on penalized regression to identify genetic variants associated with multiple mixed-type responses belonging to a specific category.

²K. Kim et al., *BMC bioinformatics* 24, 381 (2023).

1. Variable selection: Multiple mixed-type responses

- Consider a penalized regression with a sparsity-inducing penalty on the k -th response, $k = 1, \dots, q$:

$$\hat{\beta}_k^{\lambda_k}(\mathbf{X}, \mathbf{Y}_k) = \arg \min_{\beta_k \in \mathbb{R}^p} -\ell_k(\beta_k; \mathbf{X}, \mathbf{Y}_k) + P_{\lambda_k}(\beta_k),$$

where $\ell_k(\cdot)$ is the log-likelihood function corresponding to the k -th response.

- We define the number of associated responses with the j -th predictor as

$$\hat{\pi}_j(\Lambda; \mathbf{X}, \mathbf{Y}) = \sum_{k=1}^q \mathbb{I}\left(\hat{\beta}_{jk}^{\lambda_k}(\mathbf{X}, \mathbf{Y}_k) \neq 0\right),$$

where $\Lambda = (\lambda_1, \dots, \lambda_q)$ is a set of penalty parameters.

- We propose the selection score defined by its bootstrap expectation:

$$\hat{\Pi}_j(\Lambda; \mathbf{X}, \mathbf{Y}) = \mathbb{E}^*[\hat{\pi}_j(\Lambda; \mathbf{X}, \mathbf{Y})].$$

1. Variable selection: Multiple mixed-type responses

- Manhattan plot

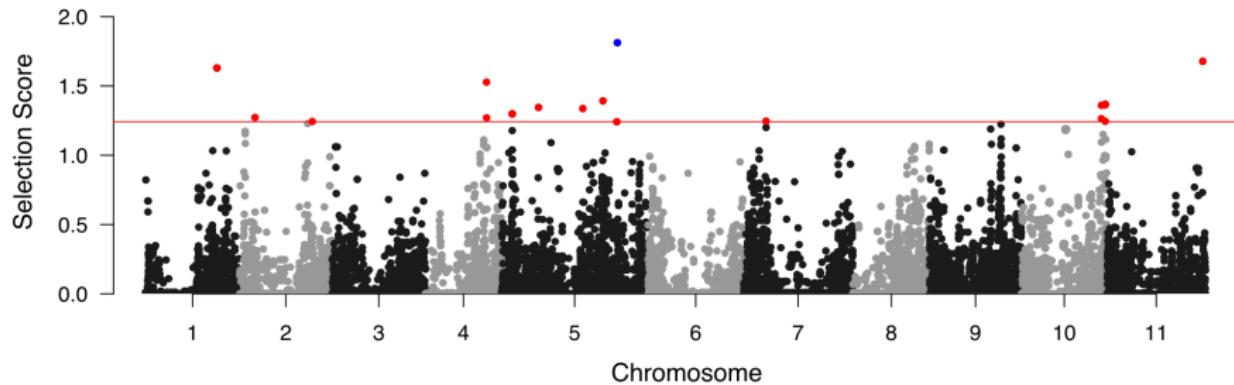


Figure: Top 20 ranked predictors are colored by red or blue.

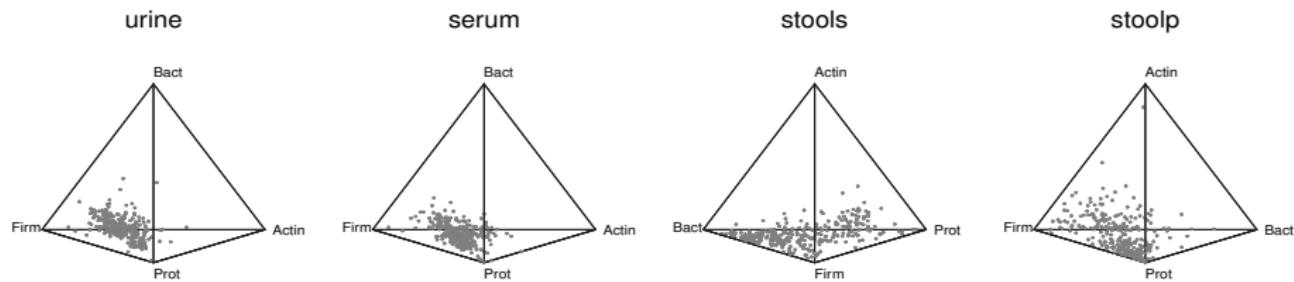
2. Non-Euclidean data analysis

Compositional data

- 16s rRNA microbiome sequencing data
 - ▶ (1) Compositionality, (2) High dimensionality, (3) Zero inflation
- The sample space is limited to a compositional space (simplex):

$$\mathbb{C}^p = \{(x_1, \dots, x_p) \in \mathbb{R}_+^p : x_1 \geq 0, \dots, x_p \geq 0; \sum_{j=1}^p x_j = 1\}.$$

- Real data example with $p = 4$:



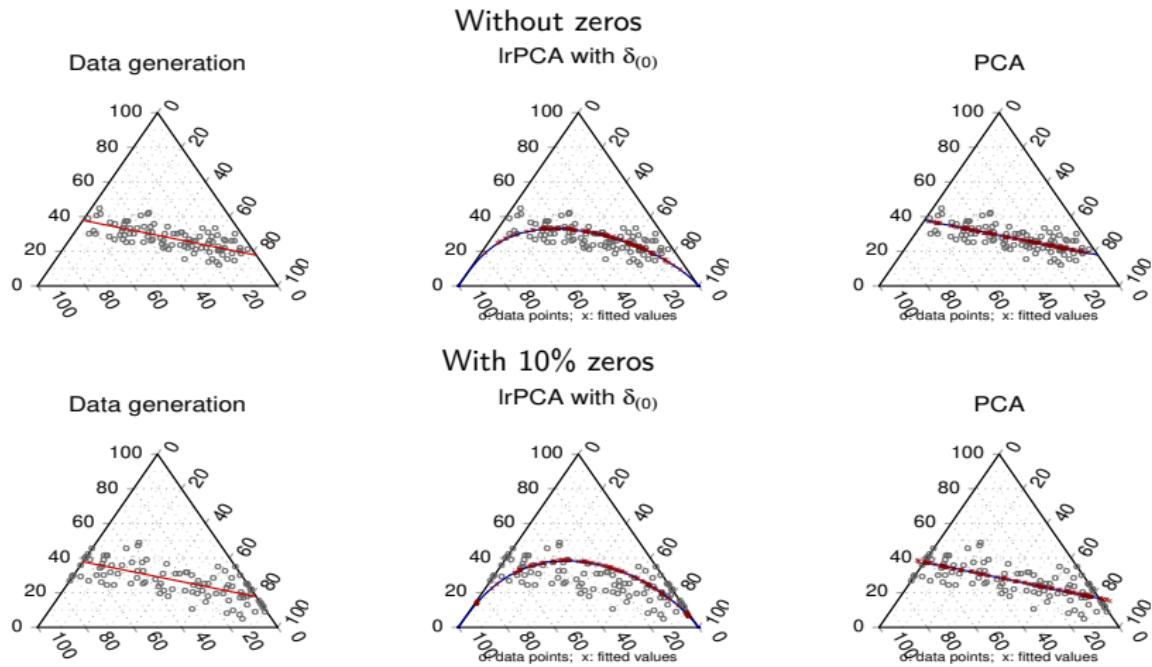
*Prot: Proteobacteria; Firm: Firmicutes; Actin: Actinobacteria; Bact: Bacteroidetes

- In this work, we aim to find a new **dimension reduction** method for zero-inflated compositional data.

2. Non-Euclidean data analysis

Motivating example: Limitation of log-ratio PCA

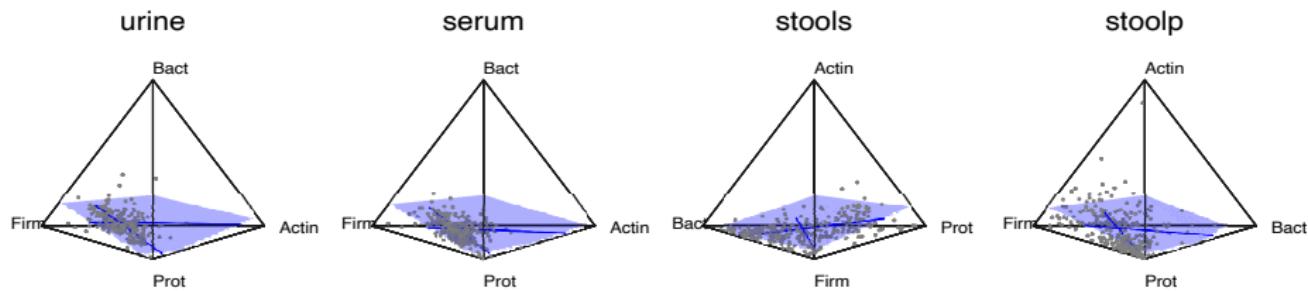
- Log-ratio PCA (IrPCA) is to apply the classical PCA after the log-ratio transformation. For dealing with zeros, some zero replacement strategies are applied. However, the zero inflation may result in **the distortion**.



2. Non-Euclidean data analysis

Principal compositional subspace

- Kim et al (2023+) aim to find a **principal compositional subspace** that best approximates the data, by minimizing the Euclidean projection error.



*Prot: Proteobacteria; Firm: Firmicutes; Actin: Actinobacteria; Bact: Bacteroidetes

- Compositional subspace spanned by $\mathbf{V}_1, \dots, \mathbf{V}_k$ at $\boldsymbol{\mu}$

$$\mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_k} := \mathbb{C}^p \cap \{ \boldsymbol{\mu} + c_1 \mathbf{V}_1, \dots, c_k \mathbf{V}_k : c_1, \dots, c_k \in \mathbb{R} \}$$

2. Non-Euclidean data analysis

Main goal

- We denote the transpose of the i -th row vector by \mathbf{a}_i and the k -th column vector by \mathbf{A}_k for a matrix \mathbf{A} .
- We want to solve the following global compositional PCA (global CPCPA) problem:

$$\arg \min_{\mathbf{U} \in \mathbb{R}^{n \times r}, \mathbf{V} \in \mathbb{R}^{p \times r}} \|\mathbf{X} - \mathbf{1}\boldsymbol{\mu}^T - \mathbf{UV}^T\|_F^2,$$

subject to

- ▶ \mathbf{U} and \mathbf{V} have orthogonal and orthonormal columns
 - ▶ $\boldsymbol{\mu} + \mathbf{Vu}_i^T \in \mathbb{C}^p \quad \forall i$ for $\boldsymbol{\mu} \in \mathbb{C}^p$
- A sequence of compositional subspaces by global CPCPA is not nested:
e.g.

$$\mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_{k-1}} \not\subseteq \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_{k-1}, \mathbf{V}_k}.$$

2. Non-Euclidean data analysis

Estimation techniques

- (Direction) Construction of a nested sequence of principal compositional subspaces:

$$\{\boldsymbol{\mu}\} \subset \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1}^p \subset \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \mathbf{V}_2}^p \subset \cdots \subset \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_k}^p \subset \cdots$$

- (Score) Projection onto principal compositional subspace:

$$\mathbf{u}_i = \Pi_{\mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_k}^p}(\mathbf{x}_i; \boldsymbol{\mu})$$

such that $\boldsymbol{\mu} + u_{i1}\mathbf{V}_1 + \cdots + u_{ik}\mathbf{V}_k \in \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_k}^p$

for $\mathbf{x}_i \in \mathbb{C}^p$ and $\mathbf{V}_1, \dots, \mathbf{V}_k \perp \mathbf{1}_p$.

2. Non-Euclidean data analysis

Sequential estimation procedure

- With the appropriate constraints,

- Rank-1 case:

$$(\hat{\mathbf{U}}, \hat{\mathbf{V}}_1) = \arg \min_{\mathbf{U}_1, \mathbf{V}_1} \|\mathbf{X} - \mathbf{1}\boldsymbol{\mu}^T - \mathbf{U}_1 \mathbf{V}_1^T\|_F^2,$$

- Rank-2 case:

$$(\hat{\mathbf{U}}, \hat{\mathbf{V}}_2) = \arg \min_{(\mathbf{U}_1, \mathbf{U}_2), \mathbf{V}_2} \|\mathbf{X} - \mathbf{1}\boldsymbol{\mu}^T - \mathbf{U}_1 \hat{\mathbf{V}}_1^T - \mathbf{U}_2 \mathbf{V}_2^T\|_F^2,$$

⋮

- Rank- k case:

$$(\hat{\mathbf{U}}, \hat{\mathbf{V}}_k) = \arg \min_{(\mathbf{U}_1, \dots, \mathbf{U}_k), \mathbf{V}_k} \|\mathbf{X} - \mathbf{1}\boldsymbol{\mu}^T - \mathbf{U}_1 \hat{\mathbf{V}}_1^T - \cdots - \mathbf{U}_k \mathbf{V}_k^T\|_F^2,$$

2. Non-Euclidean data analysis

Two types of projection approaches

- One-dimensional projection

$$\Pi_{\mathbf{v}}^{one}(\mathbf{x}_i; \boldsymbol{\mu}) = \arg \min_{u_i \in \mathbb{R}} \|\mathbf{x}_i - \boldsymbol{\mu} - u_i \mathbf{v}\|_2^2 \quad \text{subject to } \boldsymbol{\mu} + u_i \mathbf{v} \in \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{v}}$$

- Multi-dimensional projection

$$\begin{aligned} \Pi_{\mathbf{V}_1, \dots, \mathbf{V}_k}^{mult}(\mathbf{x}_i; \boldsymbol{\mu}) &= \arg \min_{u_{i1}, \dots, u_{ik} \in \mathbb{R}} \|\mathbf{x}_i - \boldsymbol{\mu} - u_{i1} \mathbf{V}_1 - \dots - u_{ik} \mathbf{V}_k\|_2^2 \\ \text{subject to } \boldsymbol{\mu} + u_{i1} \mathbf{V}_1 + \dots + u_{ik} \mathbf{V}_k &\in \mathbb{CS}_{\boldsymbol{\mu}; \mathbf{V}_1, \dots, \mathbf{V}_k} \end{aligned}$$

2. Non-Euclidean data analysis

Three proposed methods

- Compositional Reconstructed PCA (crPCA):

Given $\hat{\mu}, \hat{\mathbf{V}}_1^{PC}, \dots, \hat{\mathbf{V}}_r^{PC}$,

$$\arg \min_{\mathbf{U}_1, \dots, \mathbf{U}_r} \|\mathbf{X} - \mathbf{1}\hat{\mu}^T - \mathbf{U}_1\hat{\mathbf{V}}_1^{PC T} - \dots - \mathbf{U}_r\hat{\mathbf{V}}_r^{PC T}\|_F^2,$$

subject to

$$\hat{\mu} + u_{i1}\hat{\mathbf{V}}_1^{PC} + \dots + u_{ir}\hat{\mathbf{V}}_r^{PC} \in \mathbb{CS}_{\hat{\mu}; \hat{\mathbf{V}}_1^{PC}, \dots, \hat{\mathbf{V}}_r^{PC}} \quad \forall i$$

2. Non-Euclidean data analysis

Three proposed methods

- Compositional PCA (CPCA):

Given $\hat{\mu}, \hat{\mathbf{V}}_1, \dots, \hat{\mathbf{V}}_{k-1}$,

$$\arg \min_{\mathbf{U}_1, \dots, \mathbf{U}_k, \mathbf{V}_k} \|\mathbf{X} - \mathbf{1}\hat{\mu}^T - \mathbf{U}_1\hat{\mathbf{V}}_1^T - \dots - \mathbf{U}_{k-1}\hat{\mathbf{V}}_{k-1}^T - \mathbf{U}_k\mathbf{V}_k^T\|_F^2,$$

subject to

$$\hat{\mu} + u_{i1}\hat{\mathbf{V}}_1 + \dots + u_{ik-1}\hat{\mathbf{V}}_{k-1} + u_{ik}\mathbf{V}_k \in \mathbb{CS}_{\hat{\mu}; \hat{\mathbf{V}}_1, \dots, \hat{\mathbf{V}}_{k-1}, \mathbf{V}_k} \quad \forall i$$

$$\mathbf{V}_k \perp \mathbf{1}_p, \hat{\mathbf{V}}_1, \dots, \hat{\mathbf{V}}_{k-1}, \|\mathbf{V}_k\|_2 = 1$$

2. Non-Euclidean data analysis

Three proposed methods

- Approximated CPCCA (aCPCA):

Given $\hat{\mu}, (\hat{\mathbf{U}}_1, \hat{\mathbf{V}}_1), \dots, (\hat{\mathbf{U}}_{k-1}, \hat{\mathbf{V}}_{k-1})$,

$$\arg \min_{\mathbf{U}_k, \mathbf{V}_k} \|\mathbf{X} - \mathbf{1}\hat{\mu}^T - \hat{\mathbf{U}}_1\hat{\mathbf{V}}_1^T - \cdots - \hat{\mathbf{U}}_{k-1}\hat{\mathbf{V}}_{k-1}^T - \mathbf{U}_k\mathbf{V}_k^T\|_F^2,$$

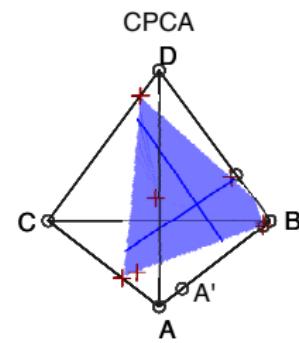
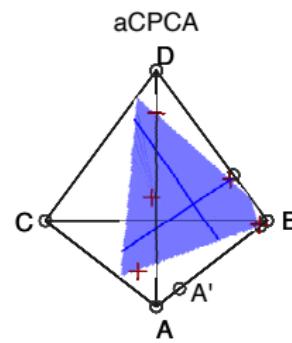
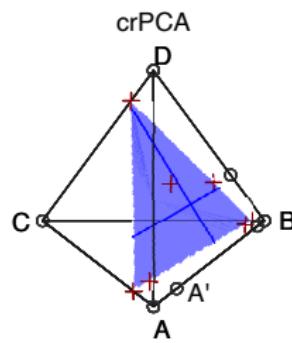
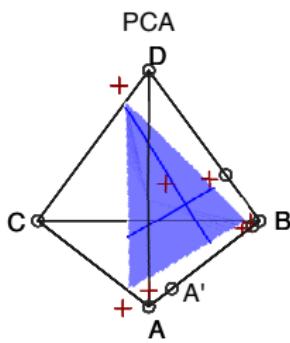
subject to

$$\hat{\mu} + \hat{u}_{i1}\hat{\mathbf{V}}_1 + \cdots + \hat{u}_{ik-1}\hat{\mathbf{V}}_{k-1} + u_{ik}\mathbf{V}_k \in \mathbb{CS}_{\hat{\mu}; \hat{\mathbf{V}}_1, \dots, \hat{\mathbf{V}}_{k-1}, \mathbf{V}_k} \quad \forall i$$

$$\mathbf{V}_k \perp \mathbf{1}_p, \hat{\mathbf{V}}_1, \dots, \hat{\mathbf{V}}_{k-1}, \|\mathbf{V}_k\|_2 = 1$$

2. Non-Euclidean data analysis

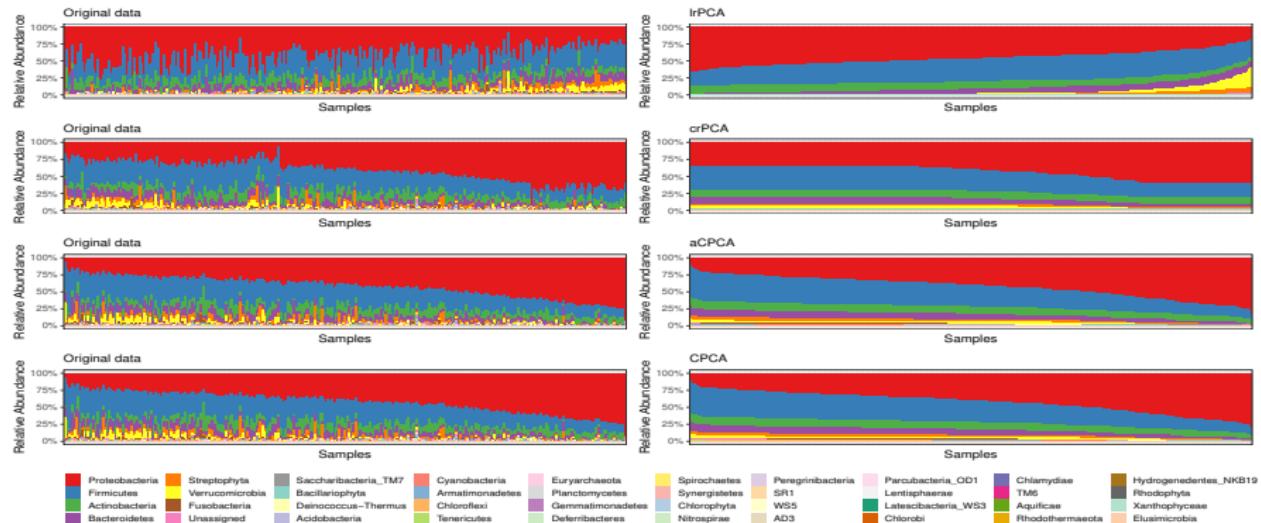
An illustrative comparison



2. Non-Euclidean data analysis

Rank-1 approximation

- The existing log-ratio PCA can have distortion in its reconstruction.



2. Non-Euclidean data analysis

Theoretical properties

Theorem (Existence)

The principal compositional subspaces and principal compositional directions ($\mathbb{CS}_{\mu; \mathbf{v}_1, \dots, \mathbf{v}_k}$, V_k , $\mathbb{CS}_{\hat{\mu}; \hat{\mathbf{v}}_1, \dots, \hat{\mathbf{v}}_k}$, and \hat{V}_k) exist for all $k = 1, \dots, p$.

Theorem (Consistency)

Assume $\mathbb{CS}_{\mu; \mathbf{v}_1, \dots, \mathbf{v}_k}$ uniquely exists for all $k = 1, \dots, p$. Then, the followings hold almost surely.

- (a) $\lim_{n \rightarrow 0} h(\mathbb{CS}_{\hat{\mu}; \hat{\mathbf{v}}_1, \dots, \hat{\mathbf{v}}_k}, \mathbb{CS}_{\mu; \mathbf{v}_1, \dots, \mathbf{v}_k}) = 0$.
- (b) $\lim_{n \rightarrow 0} \|\hat{V}_k(\mathcal{X}_n) - V_k\| = 0$.

where h is the Hausdorff distance defined by

$h(A, B) := \max \{ \sup_{a \in A} \inf_{b \in B} \|a - b\|_2, \sup_{b \in B} \inf_{a \in A} \|a - b\|_2 \}$ for nonempty closed subsets A and B of \mathbb{C}^p .

3. Multi-source data integration

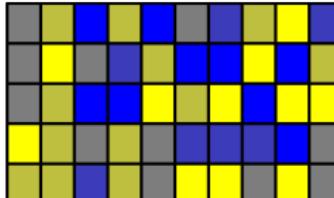
- Multi-source data is defined as a set of datasets produced from different multiple sources:
{ Gene expression, DNA methylation, RNA sequencing, ... }



- ▶ Each can be thought of as a design matrix, so we have

$$\mathbf{X} = [\mathbf{X}_{(1)}, \mathbf{X}_{(2)}, \mathbf{X}_{(3)}, \dots].$$

- Our goal is to estimate the structural relationship between multi-source data and drug responses ($q > 50$).



3. Multi-source data integration

Reduced-rank regression (RRR)

- Multivariate regression with low-rank assumption

$$\mathbf{Y}_{n \times q} = \mathbf{X}_{n \times p} \mathbf{C}_{p \times q} + \mathbf{E}_{n \times q}$$

where $\text{rank}(\mathbf{C}) = r$ and $r \leq \min\{n, p, q\}$.

- This leads to the reduced-rank regression model³:

$$\mathbf{Y}_{n \times q} = \mathbf{X}_{n \times p} \mathbf{B}_{p \times r} \mathbf{A}_{q \times r}^T + \mathbf{E}_{n \times q}.$$

- ▶ This can dramatically reduce the number of parameters to be estimated ($pq \rightarrow (p+q)r$).
- ▶ Thus, the estimates are more precise

³A. J. Izenman, *Journal of Multivariate Analysis* 5, 248–264 (1975).

3. Multi-source data integration

Structural Learning in RRR

- Goal is to identify the structured association between multiple responses and multi-source datasets

$$\mathbf{Y} = \left[\mathbf{X}_{(1)}, \mathbf{X}_{(2)}, \mathbf{X}_{(3)} \right] \begin{bmatrix} \mathbf{b}_{11} & \mathbf{b}_{12} & \mathbf{0} \\ \mathbf{b}_{21} & \mathbf{b}_{22} & \mathbf{0} \\ \mathbf{b}_{31} & \mathbf{0} & \mathbf{b}_{33} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \\ 0 & 0 & 0 \end{bmatrix}^\top + \mathbf{E},$$

- Structural relationship between \mathbf{X} to \mathbf{Y} through \mathbf{XB} :

- The first column is *joint* structure: $\mathbf{X}_{(1)}\mathbf{b}_{11} + \mathbf{X}_{(2)}\mathbf{b}_{21} + \mathbf{X}_{(3)}\mathbf{b}_{31}$
- The second column is *partially-joint* structure: $\mathbf{X}_{(1)}\mathbf{b}_{12} + \mathbf{X}_{(2)}\mathbf{b}_{22}$
- The third column is *individual* structure: $\mathbf{X}_{(3)}\mathbf{b}_{33}$

3. Multi-source data integration

Identifiability Problem

- To this end, we can consider the following penalized optimization problem:

$$\min_{\mathbf{A}, \mathbf{B}} \frac{1}{2n} \|\mathbf{Y} - \mathbf{X}\mathbf{B}\mathbf{A}^T\|_F^2 + \lambda \sum_{i=1}^d \sum_{k=1}^r \sqrt{p_i} \|\mathbf{b}_{ik}\|_2 + \nu^* \sum_{h=1}^q \|\mathbf{a}_h\|_2,$$

where $\lambda \geq 0$ controls the structured sparsity of \mathbf{B} and ν^* controls the row-wise sparsity of \mathbf{A} .

- However, the parameters are not unique up to an orthogonal matrix; For example, $\mathbf{B}\mathbf{A}^T = \mathbf{B}\mathbf{Q}\mathbf{Q}^T\mathbf{A}^T$ for $\mathbf{Q} \in \mathbb{R}^{r \times r}$ such that $\mathbf{Q}\mathbf{Q}^T = \mathbf{I}_r$.

3. Multi-source data integration

Constraint for the rotational indeterminacy

- Quartimax criterion: $\mathcal{F}(\mathbf{A}) = \sum_{j=1}^q \sum_{k=1}^r A_{jk}^4$ for a generic matrix \mathbf{A} .

Definition (Quartimax-simple structure)

Given $\mathbf{A} \in \mathbb{R}^{q \times r}$, the rotated matrix \mathbf{AQ} is said to have a *quartimax-simple structure* if \mathbf{Q} maximizes the quartimax criterion $\mathcal{F}(\mathbf{AQ})$ over all $\mathbf{Q} \in \mathcal{O}(r)$. Also, a set of semi-orthogonal matrices with simple structure is defined as

$$\mathcal{O}_S(q, r) = \left\{ \mathbf{A}\hat{\mathbf{Q}} : \hat{\mathbf{Q}} = \arg \max_{\mathbf{Q} \in \mathcal{O}(r)} \mathcal{F}(\mathbf{AQ}), \mathbf{A} \in \mathcal{O}(q, r) \right\}.$$

where $\mathcal{O}(r) = \left\{ \mathbf{Q} \in \mathbb{R}^{r \times r} : \mathbf{Q}^T \mathbf{Q} = \mathbf{QQ}^T = \mathbf{I}_r \right\}$ and
 $\mathcal{O}(q, r) = \left\{ \mathbf{A} \in \mathbb{R}^{q \times r} : \mathbf{A}^T \mathbf{A} = \mathbf{I}_r \right\}.$

3. Multi-source data integration

Constrained reduced-rank regression model

- We propose the constrained reduced-rank regression model with the condition $\mathbf{A} \in \mathcal{O}_S(q, r)$:

$$\mathbf{Y} = \mathbf{X}\mathbf{B}\mathbf{A}^T + \mathbf{E}, \quad \mathbf{A} \in \mathcal{O}_S(q, r), \quad (1)$$

where $\mathbf{E} = (\mathbf{e}_1, \dots, \mathbf{e}_n)^T$ with $\mathbf{e}_l \sim \mathcal{N}_q(\mathbf{0}, \sigma^2 \mathbf{I})$, $l = 1, \dots, n$.

- The following proposition illustrates the identifiability of (1).

Proposition

In model (1), if $\mathbf{B}^T \mathbf{X}^T \mathbf{X} \mathbf{B}$ has r distinct positive eigenvalues for the fixed design matrix \mathbf{X} , then the parameter set $(\mathbf{A}, \mathbf{X}\mathbf{B}, \sigma^2)$ is identifiable up to simultaneous signed permutations of the columns of \mathbf{A} and $\mathbf{X}\mathbf{B}$.

3. Multi-source data integration

Identifiability under RE condition

- We need the identifiability of \mathbf{B} , not \mathbf{XB} .
- Under the restricted eigenvalue condition⁴ on \mathbf{X} , we have the following corollary.

Corollary

Assume that \mathbf{B} has at most s nonzero elements. If the design matrix $\mathbf{X} \in \mathbb{R}^{n \times p}$ satisfies the RE condition over $\mathbb{C}(2s, \xi)$ for some $\xi > 0$, the set of parameters $(\mathbf{A}, \mathbf{B}, \sigma^2)$ is identifiable up to simultaneous signed permutations of the columns.

⁴P. J. Bickel et al., *The Annals of Statistics* 37, 1705–1732 (2009).

3. Multi-source data integration

Integrative Sparse Reduced-Rank Regression (iSRRR)

- Kim and Jung (2024)⁵ propose to estimate \mathbf{A} and \mathbf{B} for integrative sparse reduced-rank regression (iSRRR) by solving the constrained optimization problem

$$\min_{\mathbf{A}, \mathbf{B}} \frac{1}{2n} \|\mathbf{Y} - \mathbf{X}\mathbf{B}\mathbf{A}^T\|_F^2 + \lambda \sum_{i=1}^d \sum_{k=1}^r \sqrt{p_i} \|\mathbf{b}_{ik}\|_2$$

subject to $\mathbf{A} \in \mathcal{O}_S(q, r)$ and $\mathbf{A} \in \mathcal{T}(\nu)$,

$$\text{where } \mathcal{T}(\nu) = \left\{ \mathbf{A} \in \mathcal{O}(q, r) : \min_{j: \mathbf{a}_j \neq \mathbf{0}} \|\mathbf{a}_j\|_2 \geq \nu \right\}.$$

⁵K. Kim, S. Jung, *Statistics and Computing* 34, 2 (2024).

Future Research Plan

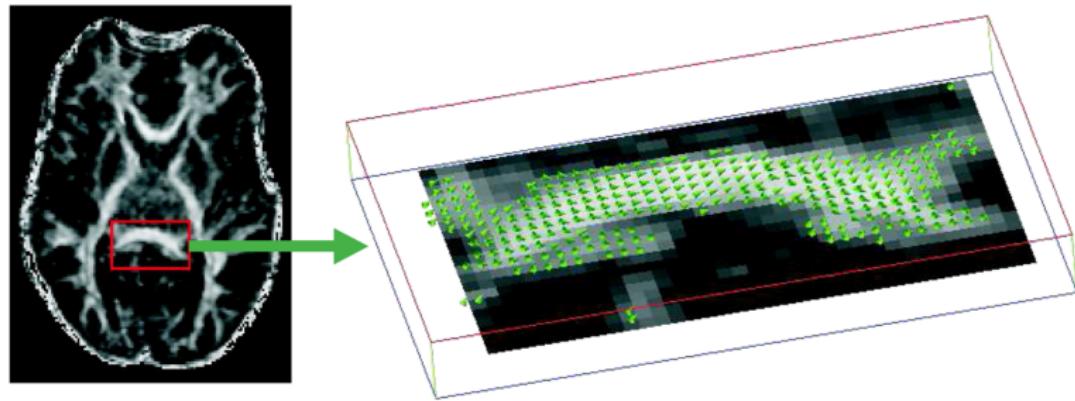
Future Research Plan

- Current research areas
 - ▶ Variable selection in high-dimensional genomic data
 - ▶ Low-rank model for non-Euclidean data
 - ▶ Multi-source data integration
- Future research topics of interest
 - ▶ **Large-scale cohort data analysis** (in the long term)
 - e.g. UK biobank data with 500,000 individuals
 - Transfer learning from large-scale data to smaller data of interest.
 - ▶ **Non-Euclidean data integration**

Non-Euclidean data integration

Spherical data

- Diffusion Tensor Imaging (DTI) data



6

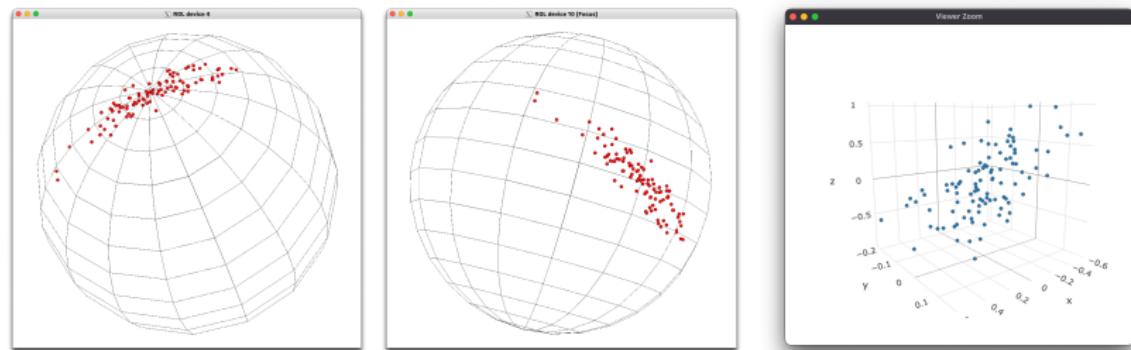
- DTI data collects the directions for the movements of water molecules at multiple brain regions.
- The direction can be represented by a vector with unit norm.

⁶V. Koltchinskii et al. (2007).

Non-Euclidean data integration

Spherical data

- Spherical data refers to data that is distributed on the surface of a hyper-sphere.
- Structural decomposition for multiple datasets (ongoing):



- We expect to be able to correlate functional differences in the brain with other biological data.

Non-Euclidean data integration

Joint and Individual Variation Explained (JIVE) model

- JIVE model for gaussian-valued data

$$\begin{bmatrix} \mathbf{X}_{(1)}^T \\ \vdots \\ \mathbf{X}_{(D)}^T \end{bmatrix} = \begin{bmatrix} \boldsymbol{\mu}_{(1)} \\ \vdots \\ \boldsymbol{\mu}_{(D)} \end{bmatrix} \mathbf{1}_n^T + \begin{bmatrix} \mathbf{V}_{(1)} \\ \vdots \\ \mathbf{V}_{(D)} \end{bmatrix} \mathbf{U}_{(0)}^T + \begin{bmatrix} \mathbf{A}_{(1)} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{A}_{(D)} \end{bmatrix} \begin{bmatrix} \mathbf{U}_{(1)}^T \\ \vdots \\ \mathbf{U}_{(D)}^T \end{bmatrix} + \begin{bmatrix} \mathbf{E}_{(1)} \\ \vdots \\ \mathbf{E}_{(D)} \end{bmatrix}$$

- For the d -th source case:

$$\mathbf{X}_{(d)} = \mathbf{1}\boldsymbol{\mu}_{(d)}^T + \mathbf{U}_{(0)}\mathbf{V}_{(d)}^T + \mathbf{U}_{(d)}\mathbf{A}_{(d)}^T,$$

where $\mathbf{U}_{(0)} \in \mathbb{R}^{n \times r_0}$, $\mathbf{V}_{(d)} \in \mathbb{R}^{p \times r_0}$, $\mathbf{U}_{(d)} \in \mathbb{R}^{n \times r_d}$, $\mathbf{A}_{(d)} \in \mathbb{R}^{p \times r_d}$

Non-Euclidean data integration

JIVE for non-Euclidean case

- $X_{ij}^{(d)} \sim$ Exponential family with the natural parameter $\theta_{ij}^{(d)}$
- For spherical data, we use the von Mises-Fisher (vMF) distribution:

$$f_{\text{vmf}}(\mathbf{x}; \boldsymbol{\theta}, \kappa) = C_p(\kappa) \exp(\kappa \cdot \boldsymbol{\theta}^T \mathbf{x})$$

- $g(\mathbb{E} X_{ij}^{(d)}) = \theta_{ij}^{(d)} = \boldsymbol{\mu}_j^{(d)} + \mathbf{u}_i^{(0)T} \mathbf{v}_j^{(d)} + \mathbf{u}_i^{(d)T} \mathbf{a}_j^{(d)}$

- Matrix-version

$$\boldsymbol{\Theta}_{(d)} = \mathbf{1}_n \boldsymbol{\mu}_{(d)}^T + \mathbf{U}_{(0)} \mathbf{V}_{(d)}^T + \mathbf{U}_{(d)} \mathbf{A}_{(d)}^T,$$

where $\mathbf{U}_{(0)} \in \mathbb{R}^{n \times r_0}$, $\mathbf{V}_{(d)} \in \mathbb{R}^{p \times r_0}$, $\mathbf{U}_{(d)} \in \mathbb{R}^{n \times r_d}$, $\mathbf{A}_{(d)} \in \mathbb{R}^{p \times r_d}$

- Estimate each of $\mathbf{U}_{(0)}$, $\mathbf{V}_{(d)}$, $\mathbf{U}_{(d)}$ and $\mathbf{A}_{(d)}$ with others fixed

Future Research Plan

- Collaboration with many researchers in various fields:
 - ▶ Dept. of Statistics, Pusan/Seoul National Univ.
 - ▶ Data Discovery Science Institute, Seoul National Univ.
 - ▶ Korea National Institute of Health (KNIH)
 - ▶ Center for Happiness Studies, Seoul National Univ.
 - ▶ School of Medicine, Pusan National Univ.
- By leveraging these collaborative relationships, we aim to successfully secure research grants and publish good results in the future.

Thank you for your attention

