Canonical Correlations for Group Symmetry Models

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- Developed by Hotelling (1936).
- Theory covered in Chapter 12 of Anderson (1984).

 \bullet

- \bullet X_1, \ldots, X_N are i.i.d. normally distributed random vectors with mean zero and covariance matrix $\Sigma \in \text{PD}(I)$.
- $\mathbb{R}^I = \mathbb{R}^{J_1} \oplus \mathbb{R}^{J_2}$

 $X_n =$ $\left(X_n^{(1)}\right)$ *X* (2) *n* \setminus

Testing problem: are $X_n^{(1)}$ and $X_n^{(2)}$ independent?

• Suppose
$$
x \in \mathbb{R}^{J_1}
$$
 and $y \in \mathbb{R}^{J_2}$

Linear combinations: $x^t X_n^{(1)}$ and $y^t X_n^{(2)}$

•
$$
Cov_{\Sigma}(x, y) := x^{t} \Sigma_{12} y
$$

$$
\bullet \ \mathbb{V}_{\Sigma}(x) := x^t \Sigma_{11} x
$$

$$
\bullet \ \mathbb{V}_{\Sigma}(y) := y^t \Sigma_{22} y
$$

- The *first canonical correlation* is
- $c_1 = \max\{ \text{Cov}_{\Sigma}(x, y) \, \big| \, x \in \mathbb{R}^{J_1}, y \in \mathbb{R}^{J_2}, \mathbb{V}_{\Sigma}(x) = \mathbb{V}_{\Sigma}(y) = 1 \}.$
- Suppose the maximum is attained at (x_1, y_1) .
- (*x*1, *y*1) is the *first pair of canonical covariates*.

Definitions

The *second canonical correlation* is

$$
c_2 = \max\{Cov_{\Sigma}(x, y) \mid x \in \mathbb{R}^{J_1}, y \in \mathbb{R}^{J_2}, \mathbb{V}_{\Sigma}(x) = \mathbb{V}_{\Sigma}(y) = 1, \\ Cov_{\Sigma}(x, x_1) = Cov_{\Sigma}(y, y_1) = 0 \},
$$

Max is attained at (x_2, y_2) , the *second pair of canonical covariates*.

The *k*th *canonical correlation* is

$$
c_k = \max\{Cov_\Sigma(x, y) \mid x \in \mathbb{R}^{J_1}, y \in \mathbb{R}^{J_2}, \mathbb{V}_\Sigma(x) = \mathbb{V}_\Sigma(y) = 1, \\ Cov_\Sigma(x, x_i) = Cov_\Sigma(y, y_i) = 0, i = 1, \ldots, k - 1\},\
$$

. . .

Max is attained at (*x^k* , *y^k*), the *k*th *pair of canonical covariates*.

Results

- Canonical correlations: c_1, \ldots, c_{J_2}
- Canonical covariate pairs: $(x_1, y_1), \ldots, (x_{J_2}, y_{J_2})$.

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Theorem

c^k is the kth largest root of

$$
\begin{vmatrix} -c\Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -c\Sigma_{22} \end{vmatrix} = 0,
$$

and the canonical covariates satisfy

$$
\left(\begin{array}{cc}-c_k\Sigma_{11}&\Sigma_{12}\\ \Sigma_{21}&-c_k\Sigma_{22}\end{array}\right)\left(\begin{array}{c}x_k\\ y_k\end{array}\right)=0.
$$

Proof.

*c*¹ is the maximum value of *x ^t*Σ12*y* subject to the constraints

- $x^t\Sigma_{11}x=1$
- y ^{*t*}Σ₂₂*y* = 1

• Apply Lagrange multipliers to prove results for c_1 and (x_1, y_1) . • Complete proof by inducting on J_2 .

۰

$$
A=\left(\begin{array}{cc}A_1&0\\0&A_2\end{array}\right),\;A_1\in\text{GL}(J_1),\;A_2\in\text{GL}(J_2)
$$

• Group Actions:

$$
\blacktriangleright A \cdot x = Ax, \text{ for } x \in \mathbb{R}^{1 \times N}
$$

- \blacktriangleright *A* ⋅ Σ = *A*Σ*A^t*, for Σ ∈ **PD**(*I*)
- **•** Testing problem is invariant under these actions
- The family of *empirical* canonical correlations is a maximal invariant statistic.

Empirical Canonical Correlations and Eigenvalues

 $\hat{\Sigma} = S = \left(\begin{array}{cc} S_{11} & S_{12} \ S_{21} & S_{22} \end{array} \right)$ $\hat{\Sigma}_0 = \left(\begin{array}{cc} \mathcal{S}_{11} & 0 \ 0 & \mathcal{S}_{22} \end{array} \right)$

• Residual

0

 \bullet

 \bullet

$$
\mathit{R}=\hat{\Sigma}-\hat{\Sigma}_0=\left(\begin{array}{cc}0 & S_{12}\\ S_{21} & 0\end{array}\right)
$$

Empirical canonical correlations satisfy

$$
\left|\begin{array}{cc}-c_{k}S_{11}&S_{12}\\S_{21}&-c_{k}S_{22}\end{array}\right|=0
$$

$$
|R - c_k \hat{\Sigma}_0| = 0
$$

Empirical Canonical Correlations and Eigenvalues

 \bullet

$$
|R-c_k\hat\Sigma_0|=0
$$

- Empirical canonical correlations are eigenvalues of R wrt. $\hat{\Sigma}_0$.
- Canonical covariates satisfy

$$
(R - c_k \hat{\Sigma}_0) \left(\begin{array}{c} x_k \\ y_k \end{array}\right) = 0
$$

 \bullet

 \bullet

$$
u_k = \frac{1}{2} \begin{pmatrix} x_k \\ y_k \end{pmatrix}
$$
 is an eigenvector of *R* wrt. $\hat{\Sigma}_0$ corresponding to c_k

$$
v_k = \frac{1}{2} \begin{pmatrix} x_k \\ -y_k \end{pmatrix}
$$
 is an eigenvector corresponding to $-c_k$

Empirical Canonical Covariates and Eigenvectors

$$
\bullet \; x_k = u_k + v_k
$$

$$
\bullet \ \ y_k = u_k - v_k
$$

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[Canonical Correlations](#page-2-0)

- Theory: Andersson and Madsen (1998), Appendix A
- Ten Fundamental Testing Problems: Andersson, Brøns, and Jensen (1983)

Pattern Covariance Matrices

Testing covariance structure of a multivariate normal distribution.

Example (Testing Complex Structure)

$$
H_0: \Sigma = \left(\begin{array}{cc} A & -B \\ B & A \end{array}\right)
$$

Example (Testing Independence)

$$
H_0: \Sigma = \left(\begin{array}{cc} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{array}\right)
$$

Example (Bartlett's Test)

$$
H_0: \Sigma = \left(\begin{array}{cc}\Gamma & 0 \\ 0 & \Gamma\end{array}\right) \text{ vs. } H: \Sigma = \left(\begin{array}{cc}\Sigma_{11} & 0 \\ 0 & \Sigma_{22}\end{array}\right)
$$

- $G \leq O(1)$ is a compact group
- $GL_G(I) = \{$ Invertible matrices that commute with $G\}$
- **PD** $_G(I) = \{Positive definite matrices that commute with G\}$

Group Symmetry Model X_1, X_2, \ldots, X_N i.i.d. Normal $(0, \Sigma)$ H_G : $\Sigma \in \mathbf{PD}_G(I)$

Example (Testing Complex Structure)

$$
G_0 = \left\{ \pm 1_J, \pm \left(\begin{array}{cc} 0 & -1_J \\ 1_J & 0 \end{array} \right) \right\}
$$

Example (Testing Independence)

$$
G_0 = \left\{ \pm 1_I, \pm \left(\begin{array}{cc} 1_{J_1} & 0 \\ 0 & -1_{J_2} \end{array} \right) \right\}
$$

Example (Bartlett's Test)

$$
G_0=\left\langle\left(\begin{array}{cc}1_J&0\\0&-1_J\end{array}\right),\left(\begin{array}{cc}0&1_J\\1_J&0\end{array}\right)\right\rangle
$$

Estimation

 \bullet $\hat{\Sigma} = \Psi_G(\mathcal{S}) = \int_G$ *gSg^t dg* \bullet $\hat{\Sigma} = \frac{1}{16}$ \sum *gSg^t* |*G*| *g*∈*G*

Example (Testing Complex Structure) $\hat{\Sigma}_0 = \frac{1}{2}$ 2 $\begin{pmatrix} S_{11} + S_{22} & S_{12} - S_{21} \ S_{21} - S_{12} & S_{11} + S_{22} \end{pmatrix}$

Σˆ ∼ generalized Wishart distribution on **PD***G*(*I*).

- \bullet *G* \le *G*₀
- $\mathsf{PD}_{G_0}(I) \subseteq \mathsf{PD}_G(I)$
- Testing problem:

$$
H_0: \Sigma \in \textbf{PD}_{G_0}(I) \text{ vs. } H: \Sigma \in \textbf{PD}_G(I)
$$

- Actions of *A* ∈ **GL***G*(*I*)
	- \blacktriangleright *A* · *x* = *Ax*, for *x* $\in \mathbb{R}^{1 \times N}$
	- \blacktriangleright *A* ⋅ Σ = *A*Σ*A^t*, for Σ ∈ **PD**_{*G*}(*I*)
- Maximal invariant: eigenvalues of $R=\hat{\Sigma}-\hat{\Sigma}_0$ wrt. $\hat{\Sigma}_0.$
- Can canonical correlations be generalized?
- Are these maximally invariant eigenvalues canonical correlations?

- \bullet *X*₁, *X*₂, . . . , *X*_{*N*} i.i.d. Normal(0, Σ)
- $\bullet \ \Theta_0 \subseteq \Theta \subseteq \mathsf{PD}(I)$
- Testing problem:

$$
H_0: \Sigma \in \Theta_0 \text{ vs. } H: \Sigma \in \Theta
$$

 \bullet *t* : $\Theta \rightarrow \Theta_0$ $\hat{\Sigma}_0 = t(\hat{\Sigma})$

$$
\bullet \ \ c_1 = \max\{ \text{Cov}_{\Sigma}(x, y) \, | \, \text{Cov}_{t(\Sigma)}(x, y) = 0, \mathbb{V}_{\Sigma}(x) = \mathbb{V}_{\Sigma}(y) = 1 \}
$$

$$
\bullet \ \ c_k = \max\{ \text{Cov}_{\Sigma}(x, y) \, \big| \, \text{Cov}_{t(\Sigma)}(x, y) = 0, \mathbb{V}_{\Sigma}(x) = \mathbb{V}_{\Sigma}(y) = 1
$$

$$
\blacktriangleright \text{ for } i=1,\ldots,k-1,
$$

$$
\sim \text{Cov}_{t(\Sigma)}(x, x_i) = \text{Cov}_{t(\Sigma)}(x, y_i) = 0,
$$

$$
\blacktriangleright \text{Cov}_{t(\Sigma)}(y, x_i) = \text{Cov}_{t(\Sigma)}(y, y_i) = 0\}
$$

Results

• Eigenvalues of
$$
\Sigma - t(\Sigma)
$$
 wrt. $t(\Sigma)$:

$$
\lambda_1 \geq \cdots \geq \lambda_l
$$

$$
\bullet
$$

$$
c_k = \frac{\lambda_k - \lambda_{k+1-k}}{\lambda_k + \lambda_{l+1-k} + 2}
$$
, for $k = 1, ..., \lfloor \frac{l}{2} \rfloor$

Covariate pairs: characterized in terms of eigenvectors

Proof.

- WLOG, $t(\Sigma) = 1$ *I* and $\Sigma t(\Sigma) = \Lambda = \text{Diag}(\lambda_1, \ldots, \lambda_l)$
- Apply Lagrange multipliers to

•
$$
c_1 = \max\{x^t \wedge y \mid x, y \in \mathbb{R}^l, x^t(1_l + \Lambda)x = y^t(1_l + \Lambda)y = 1, x^t y = 0\}
$$

Induct on *I*

- $\Theta = \mathsf{PD}_G(I)$
- $\Theta_0 = \mathsf{PD}_{G_0}(I)$
- \bullet $t = \Psi_G$

 \bullet

Eigenvalues of $\hat{\Sigma}-\hat{\Sigma}_0$ wrt. $\hat{\Sigma}_0$

$$
\lambda_1, \lambda_2, \ldots, -\lambda_2, -\lambda_1
$$

$$
c_k = \lambda_k, \text{ for } k = 1, \ldots, \lfloor \frac{l}{2} \rfloor
$$

Covariate pairs: characterized in terms of eigenvectors

- Eigenvalues related to other testing problems, such as graphical models.
- Unbiasedness of likelihood ratio tests for group symmetry models.
- Andersson, S.A., Brøns, H.K., and Tolver Jensen, S. (1983). Distribution of Eigenvalues in multivariate statistical analysis. *Ann. Statist.* **11** 392-415.
- Andersson, S.A. and Madsen, J. (1998). Symmetry and lattice conditional independence in a multivariate normal distribution. *Ann. Statist.* **26** 525-572.
- **Hotelling, Harold (1936). Relations Between Two Sets of Variates.** *Biometrika* **28** 321-377.