

# Subselect 0.9-99: Selecting variable subsets in multivariate linear models

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**THE PROBLEM:** Finding a k-variable subset that is a good surrogate for a full p-variable data set

## **CONTEXT:**

- **Exploratory data analysis – Subselect 0.1-- 0.9**  
(Cadima, Cerdeira, Duarte Silva and Minhoto -- useR! 2004)
- **Multivariate Linear Models – Subselect 0.9-99**

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## A LINEAR HYPOTHESIS FRAMEWORK

$$X = A \Psi + U \quad H_0: C \Psi = 0$$

- SELECT COLUMNS OF X IN ORDER TO EXPLAIN H1

## PARTICULAR CASES:

CANONICAL CORRELATION ANALYSIS  $A = [1 \mid Y]$   $C = [0 \mid I]$

LINEAR DISCRIMINANT ANALYSIS

$$A = [1_g] \quad \Psi = [\mu_g] \quad C = \begin{bmatrix} 1 & -1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 1 & 0 & \dots & -1 \end{bmatrix}$$

MULTI-WAY MANOVA/MANCOVA EFFECTS

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$$\Omega = \mathcal{R}(A) \quad \omega = \mathcal{R}(A) \cap \mathcal{N}(C) \quad r = \dim(\Omega) - \dim(\omega)$$

$$\mathbf{ccr}_i^2 = \text{Eigval}_i(\mathbf{T}^{-1}\mathbf{H}) \quad \mathbf{T} = \mathbf{X}'(\mathbf{I} - \mathbf{P}_\omega)\mathbf{X} \quad \mathbf{H} = \mathbf{X}'(\mathbf{P}_\Omega - \mathbf{P}_\omega)\mathbf{X}$$

## Comparison Criteria:

## Multivariate Indices

$$\mathbf{ccr}_1^2$$

$$( \max \mathbf{ccr}_1^2 \Leftrightarrow \max \text{Roy } \lambda_1 )$$

$$\tau^2 = 1 - \left( \prod_{i=1}^r (1 - \mathbf{ccr}_i^2) \right)^{1/r}$$

$$( \max \tau^2 \Leftrightarrow \min \text{Wilks } \Lambda )$$

$$\zeta^2 = 1 - \frac{r}{\sum_{i=1}^r (1 - \mathbf{ccr}_i^2)^{-1}}$$

$$( \max \zeta^2 \Leftrightarrow \max \text{Lawley-Hotelling trace} )$$

$$\xi^2 = \frac{\sum_{i=1}^r \mathbf{ccr}_i^2}{r}$$

$$( \max \xi^2 \Leftrightarrow \max \text{Bartleii-Pillai trace} )$$

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## The Subselect Package

Search routines for (combinatorial) criteria optimization

### Exact Algorithm:

- leaps** - based on Furnival and Wilson's leaps and bounds algorithm for linear regression
  - viable with up to 30 - 35 original variables

### Heuristics:

- anneal** - simulated annealing
- genetic** - genetic algorithm
- improve** - restricted local improvement

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### Principal arguments of search routines :

- mat** - Total SSCP data matrix (T)
- H** - Effect SSCP data matrix
- r** - Expected rank of the H matrix
- criterion** - “ccr12”, “tau2”, “xi2” or “zeta2”
- kmin, kmax** - minimum and maximum subset dimensionalities sought

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### Other arguments :

- Tuning parameters for heuristics
- Maximum time allowed for exact search
- Variables forcibly included or excluded in the selected subsets
- Number of solutions by subset dimensionality
- Numerical tolerance for detecting singular or non-symmetrical matrices

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### Auxiliary functions:

- lmHmat** - creates H and mat matrices for linear regression/canonical correlation analysis
- ldaHmat** - creates H and mat matrices for linear discriminant analysis
- glhHmat** - creates H and mat matrices for an analysis based on a linear hypothesis specified by the user

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### Auxiliary functions :

**ccr12.coef, tau2.coef**  
**zeta2.coef, xi2.coef**

- computes a comparison  
criterion for a subset  
supplied by the user

**trim.matrix**

- deletes rows and columns of singular or ill-conditioned matrices
- until all linear dependencies (perfect or almost perfect) are removed

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## Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

### Description:

58 pits were analyzed before (1983) and after (1986) harvesting (83-84) trees larger than a minimum diameter

Continuous variables: gr/m<sup>2</sup> of exchangeable cations

Al - Aluminum

K - Potassium

Ca - Calcium

Na - Sodium

Mg - Magnesium

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## Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

### Factors:

### Factor levels:

	1 - Spruce- fir
F - Forest Type	2 - High elevation hardwood
	3 - Low elevation hardwood
	0 - Uncut forest
D - Logging Disturbance	1 - Cut, undisturbed by machinery
	2 - Cut, disturbed by machinery
Year	1983 or 1986

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## Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

### Reading and preparing the data:

```
> library(subselect)
> HubForest <- read.table("Hubbard Brook.txt", header=T,
  col.names=c("Pit", "F", "D", "Al", "Ca", "Mg", "K", "Na", "Year"),
  colClasses=c("factor", "factor", "factor", "numeric",
    "numeric", "numeric", "numeric", "numeric", "factor"))
```

### Analysis #1: Explaining the levels of calcium

```
> Hmat <- lmHmat(Ca ~ F*D + Al + Mg + K + Na, HubForest)
> colnames(Hmat$mat)
> leaps(Hmat$mat, H=Hmat$H, r=1, nsol=3)
```

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## Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

**Analysis #2:** Looking for combinations of Forest type and Disturbance that best explain the nutrient levels

```
> Hmat <- lmHmat(cbind(Al,Ca,Mg,K,Na) ~ F*D,HubForest)
> colnames(Hmat$mat)
> leaps(Hmat$mat,H=Hmat$H,r=5,criterion="tau2",nsol=3)
```

**Analysis #3:** Finding which subsets of nutrients were most affected by the harvesting in 1983-84

```
> Hmat <- ldaHmat(Year ~ Al + Ca + Mg + K + Na , HubForest)
> leaps(Hmat$mat,H=Hmat$H,r=1,nsol=3)
```

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## Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

Analysis #4: Finding which subsets of nutrients are most affected by interactions between harvesting and logging disturbances, after controlling for the effect of forest type

- > C <- matrix(0.,2,8)
- > C[1,7] = C[2,8] = 1.
- > Hmat <- glhHmat(cbind(Al,Ca,Mg,K,Na) ~ D\*Year + F, C, HubForest)
- > leaps(Hmat\$mat,H=Hmat\$H,r=2, criterion="tau2", nsol=3,tolsym=1E-10)

## References

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Morrison D.F. (1990). *Multivariate Statistical Methods*, 3rd ed., McGraw-Hill. New York, NY.