

## MULTIVARIATE STATISTICS, Lesson 11.

### Correspondence Analysis

(Discrete version of the canonical correlation analysis)

We have two – usually not independent – discrete (categorical) r.v.'s  $X$  and  $Y$  taking on  $n$  and  $m$  different values, respectively (e.g., hair-color and eye-color). The joint distribution  $R$  is estimated from the joint frequencies based on  $N$  observations:

$$r_{ij} = \frac{f_{ij}}{N} \quad (i = 1, \dots, n; j = 1, \dots, m).$$

Let  $\mathbf{R}$  denote the  $n \times m$  matrix of  $r_{ij}$ 's. The marginal distributions  $P$  and  $Q$  are:

$$p_i = r_{i.} \quad (i = 1, \dots, n) \quad \text{and} \quad q_j = r_{.j} \quad (j = 1, \dots, m).$$

Let  $\mathbf{P}$  and  $\mathbf{Q}$  denote the  $n \times n$  and  $m \times m$  diagonal matrices containing the marginal probabilities in their main diagonals, respectively.

- **Problem:** to approximate the table  $\mathbf{R}$  with a lower rank table. For this purpose we are looking for *correspondence factor pairs*  $\alpha_l, \beta_l$  taking on values and having unit variance with respect to the marginal distributions, further being maximally correlated on certain constraints.  $\mathbb{E}_R \alpha \beta$  is maximum (1) for the trivial (constantly 1) variable pair  $\alpha_1, \beta_1$ . Then for  $k = 2, \dots, \min\{n, m\}$  we are looking for the maximum of  $\mathbb{E}_R \alpha \beta$  on the constraints that

$$\mathbb{E}_P \alpha = \mathbb{E}_Q \beta = 0, \quad \mathbb{D}_P^2 \alpha = \mathbb{D}_Q^2 \beta = 1, \quad \text{Cov}_P \alpha \alpha_i = \text{Cov}_Q \beta \beta_i = 0 \quad (i = 1, \dots, k-1).$$

- **Solution:** by the SVD of the  $n \times m$  matrix  $\mathbf{B} = \mathbf{P}^{-1/2} \mathbf{R} \mathbf{Q}^{-1/2} = \sum_{l=1}^r s_l \mathbf{v}_l \mathbf{u}_l^T$ , where  $r$  is the rank of  $\mathbf{R}$ . The singular values  $1 = s_1 \geq s_2 \geq \dots \geq s_r > 0$  are the correlations of the correspondence factor pairs, while the values taken on by the  $k$ -th pair are coordinates of the *correspondence vectors*  $\mathbf{P}^{-1/2} \mathbf{v}_k$  and  $\mathbf{Q}^{-1/2} \mathbf{u}_k$ , respectively.
- **Hypothesis testing:** to test the independence of  $X$  and  $Y$ , the test statistic

$$t = N \sum_{i=1}^n \sum_{j=1}^m \frac{(r_{ij} - p_i q_j)^2}{p_i q_j} = N \left[ \sum_{i=1}^n \sum_{j=1}^m \frac{r_{ij}^2}{p_i q_j} - 1 \right] = N \|\mathbf{B} - \mathbf{B}_1\|_F^2 = N \sum_{l=2}^r s_l^2$$

is used, that under independence follows  $\chi^2((n-1)(m-1))$ -distribution. To test the hypothesis that a  $k$ -rank approximation of the contingency table suffices, the statistic

$$N \|\mathbf{B} - \mathbf{B}_k\|_F^2 = N \sum_{l=k+1}^r s_l^2, \quad k = 1, \dots, r-1$$

should take on „small values” (its distribution is yet unknown), where  $\mathbf{B}_k = \sum_{l=1}^k s_l \mathbf{v}_l \mathbf{u}_l^T$  is the best  $k$ -rank approximation of  $\mathbf{B}$  in Frobenius norm (in spectral norm, too).

- **Definition:** The above  $t$  is called *total correspondence* of the table, while  $N \sum_{l=2}^k s_l^2 / t$  is called *correspondence explained by the first  $k$  correspondence factor pairs*.
- **Spatial representation** of the row and column categories in  $k$  dimension: by the points

$$(\alpha_1(i), \alpha_2(i), \dots, \alpha_k(i)) \quad \text{and} \quad (\beta_1(j), \beta_2(j), \dots, \beta_k(j))$$

( $i = 1, \dots, n; j = 1, \dots, m$ ). Store them for further analysis.