

Independence of the Residual Quadratic Sums in the Dispersion Equation with Noncentral χ^2 -Distribution

Nikolay I. Sidnyaev, Kristina S. Andreytseva

Bauman Moscow State Technical University, Moscow, Russia E-mail: sidnyaev@yandex.ru, 9259988800@mail.ru Received May 6, 2011; revised July 1, 2011; accepted July 8, 2011

Abstract

A model adequacy test should be carried out on the basis of accurate aprioristic ideas about a class of adequate models, as in solving of practical problems this class is final. In article, the quadratic sums entering into the equation of the dispersive analysis are considered and their independence is proved. Necessary and sufficient conditions of existence of adequate models are resulted. It is shown that the class of adequate models is infinite.

Keywords: Noncentral χ^2 -Distribution, Dispersion Analysis, Adequate Models, Quadratic Sums

1. Introduction

The dispersive analysis is defined as the statistical method intended for estimation of influence of various factors on a result of experiment, so application area of this method becomes much wider. Unbiased estimate for unknown parameters is the sum of squares. The main idea of the dispersive analysis consists in splitting of this sum of squares of deviations into some components, each of which corresponds to the prospective reason of averages changing.

Let's consider decomposition of the residual sum of squares

$$Q_0 = Q_1 + Q_2$$

and we will prove independence of the summands Q_1 and Q_2 . Two theorems and four auxiliary lemmas will be necessary for the proof.

2. Preliminaries

Lemma 2.1. The rank of composition of two matrixes A and B is less or equal to minimal rank of matrixes A and B i.e.

$$r(AB) \le \min(r(A), r(B)).$$

Proof. By a rule of matrixes multiplication, columns of matrix AB are a linear combination of columns of a matrix A, then the number of linearly independent columns in AB can't surpass the number of linearly inde-

pendent columns in A; consequently

$$r(AB) \le r(A)$$
.

Doing similar reasoning for the lines (the lines of AB are a linear combination of the lines B), we will receive that $r(AB) \le r(B)$. The lemma is proved.

Consequence of the inertia law of square-law forms (about quantity of invariants): if Q = x'Ax is the square-law form with n variables $x_1, \dots x_n$ and its rank is equal to r, r(A) = r, then r linear combinations of variables $x_1, \dots x_n$ exist, for example, z_1, \dots, z_r such

that
$$Q = \sum_{i=1}^{r} \lambda_i z_i^2$$
 and every $\lambda_i = 1$ or -1 .

We will use the Kohran theorem as a simple consequence of the following theorem.

Theorem 2.1. Let
$$\sum_{i=1}^{N} y_i^2 = Q_1 + \dots + Q_s$$
, where Q_j ,

 $j=\overline{1,s}$, are the square-law form with rank n_j from variables y_1, \dots, y_N . Then the condition $n_1+n_2+\dots+n_s=N$ is a necessary and sufficient condition for existence of the orthogonal transformation z=Ay translating a vector $y=(y_1,\dots,y_N)'$ into a vector $z=(z_1,\dots,z_N)'$ in such way, that

$$Q_1 = \sum_{i=1}^{n_1} z_i^2, Q_2 = \sum_{i=n_1+1}^{n_1+n_2} z_i^2, \dots, Q_s = \sum_{i=n_1+\dots+n_{s-1}+1}^{n_1+\dots+n_s} z_i^2,$$

Prove. Necessity.

If such orthogonal transformation exists, then

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$$\sum_{i=1}^{N} y_i^2 = \sum_{i=1}^{n_1 + \dots + n_s} z_i^2$$
. The left part is the square-law form of

a rank N, and the right part is the square-law form of a rank $n_1 + n_2 + \cdots + n_s$. By the lemma 2.2, ranks of square-law forms are equal, *i.e.* $n_1 + n_2 + \cdots + n_s = N$.

Sufficiency.

As the rank Q_j is equal n_j , then from a consequence of the inertia law of square-law forms, it follows that n_j linear combinations z_1, \dots, z_{n_j} of variables y_1, \dots, y_N exist, such that $Q_j = \sum_i \lambda_i z_i^2$ where each $\lambda_i = 1$ or -1. For Q_1 indexes i have values $1, 2, \dots, n_1$; for $Q_2 - n_1 + 1, \dots, n_1 + n_2$ etc. Now, if $\sum_{i=1}^s n_i = N$, then

N linear combinations z_1, \dots, z_N exist, which in matrix designations can be written so: z = Ay.

Using a diagonal matrix $D_{N\times N}$ with diagonal elements $\lambda_1, \dots, \lambda_N$, we receive that

$$\sum_{j=1}^{s} Q_{j} = \sum_{i=1}^{N} \lambda_{i} z_{i}^{2} = z' D z = y' A' D A y.$$

On the other hand $\sum_{j=1}^{s} Q_j = \sum_{i=1}^{N} y_i^2 = y'y$. As the sym-

metric matrix of the square-law form is unique, it is concluded that A'DA = I, hence, it is nondegenerate. Now we will prove that D = I. Let $\lambda_k = -1$. Then under the formula $y = A^{-1}z$ we can find the values of y_1, \dots, y_N corresponding to values $z_i = 0$ at $i \neq k$ and $z_k = 1$, and for these values

$$\sum_{i=1}^{N} y_i^2 = \sum_{i=1}^{N} \lambda_i z_i^2 = \lambda_k = -1,$$

that is impossible. Hence, D = I and A'A = I. Last equality shows that transformation z = Ay is orthogonal. The theorem is proved.

Remark. The condition $\sum_{i=1}^{s} n_i = N$ makes the square-

law forms Q_i positive definite, as at orthogonal transformation, it turns out that all their characteristic numbers are equal 0 or 1.

Theorem 2.2 [1]. Let random variables y_i , $i = \overline{1, N}$, are independent and have normal distributions $N(\eta_i, 1)$ accordingly. Let further

$$\sum_{i=1}^{N} y_i^2 = Q_1 + \dots + Q_s$$

where Q_i , $i = \overline{1,s}$, —the square-law form from variables y_1, \dots, y_N of n_i rank. Then Q_1, \dots, Q_s have independent noncentral χ^2 -distribution with n_1, \dots, n_s freedom degrees accordingly, in only case, when

 $\sum_{i=1}^{3} n_i = N \text{ . If } \delta_i \text{ is the parameter of noncentrality } Q_i,$ then the value δ_i^2 can be received by replacement y_i

on Q_i , i.e. if $Q_i = y'A_iy$, then $\delta_i^2 = \eta'A_i\eta$, where $\eta = (\eta_1, \dots, \eta_N)'$; $y = (y_1, \dots, y_N)'$.

Proof. Necessity.

If Q_1, \dots, Q_s are the independent random variables with χ^2 -distribution with n_1, \dots, n_s freedom degrees accordingly, then $\sum_{j=1}^s Q_j$ has noncentral χ^2 -distribu-

tion with $\sum_{j=1}^{s} n_j$ freedom degrees. As $\sum_{i=1}^{N} y_i^2$ has non-

central χ^2 -distribution with N freedom degrees, and

$$\sum_{i=1}^{N} y_i^2 = \sum_{j=1}^{s} Q_j \text{ , hence, } \sum_{j=1}^{s} n_j = N.$$

Sufficiency. Let $\sum_{j=1}^{s} n_j = N$. Then at orthogonal trans-

formation z = Ay (theorem 2.1), random variables z_1, \dots, z_N will be independent and normally distributed. From parities (2.1) and definitions of noncentral χ^2 -distributions follows that Q_1, \dots, Q_s have independent noncentral χ^2 -distributions with n_1, \dots, n_s freedom degrees accordingly. The theorem is proved.

3. Auxiliary Theorems and Lemmas

We will assume that the space of values of random variables is split into finite r parts s_1, \dots, s_n without the general points, and let p_1, \dots, p_n —probabilities $P_i = P\{X \in S_i\}$, $\sum P_i = 1$.

Let's assume that all $p_i > 0$. Let v_i is the number of observed values of random variables—X belongs to set s_i .

Let's consider a vector (v_1, \dots, v_r) . As a divergence measure between empirical and theoretical distribution

we will consider $\sum_{i=1}^{r} c_i \left(\frac{v_i}{n} - p_i \right)^2$, where factors c_i could be chosen random. Pearson has shown ([2,3]) that

if $c_i = \frac{n}{p_i}$, then received measure

$$\chi_n^2 = \sum_{i=1}^r \frac{n}{p_i} \left(\frac{\nu_i}{n} - p_i \right)^2 = \sum_{i=1}^r \frac{\nu_i^2}{np_i} - n$$
 (3.1)

possesses extremely simple properties.

Theorem 3.1. At $n \to \infty$, distribution χ_n^2 aspires to distribution χ^2 with r-1 degrees of freedom.

On the basis of this theorem by the set significance value α we will find the number χ_n^2 from the condition

$$P\left\{\chi^2 > \chi_\alpha^2\right\} = \alpha \tag{3.2}$$

The hypothesis H_0 is rejected, if $\chi_n^2 > \chi_\alpha^2$.

At the proof of the theorem the following lemma is required to us.

Lemma 3.1. Let v_1, \dots, v_r —the whole non-negative numbers, and $v_1 + v_2 + \dots + v_r = n$. Number of ways, by means of which n elements can be divided into r groups, the first of which contains v_1 elements, the second elements— $v_2, \dots, v_i - v_r$ elements, is equal to

$$\frac{n!}{v_1!\cdots v_n!}$$

Proof. The first group of v_1 elements can be chosen by $C_n^{v_1}$ ways. After the first group is formed, $n-v_1$ elements remain. Therefore, the second group of v_2 elements can be chosen by $C_{n-v_1}^{v_2}$ ways etc. After formation of r-1 groups, $n-v_1-\cdots v_{r-1}=v_r$ elements remain, which form the last group. Thus, the number of all possible ways by means of which n elements can be distributed on r groups, from which the first contains v_1 elements, \cdots , v_i contains v_r elements, is equal to

$$C_n^{\nu_1} \cdot C_{n-\nu_1}^{\nu_2} \cdots C_{n-\nu_1-\cdots-\nu_{r-2}}^{\nu_{r-1}}$$
.

Using the formula $C_n^k = \frac{n!}{k!(n-k)!}$, we will receive

the lemma statement.

Proof. Result of any test with probability

 $P_i = P\{X \in S_i\}$ will belong to set S_i . Therefore, on the basis of a lemma 2.1, the probability of that υ_1 values will belong to set S_1 , \cdots , υ_r values will belong to set S_r , is equal to

$$\frac{n!}{\nu_1!\nu_2!\cdots\nu_r!}P_1^{\nu_1}\cdots P_r^{\nu_r} \tag{3.3}$$

This expression, as it is easy to see, is the general member of decomposition $(P_1 + \cdots + P_r)^n$. Joint distribution of a random vector $v = (v_1, \dots, v_r)$ is set by expession (3.3) and is polynominal distribution. We will find the characteristic function with polynominal distributions. We have

$$\begin{split} Me^{i(t,\upsilon)} &= Me^{it_1\upsilon_1}\cdots e^{it_r\upsilon_r} \\ &= \sum_{\substack{\upsilon_l\neq 0\\\upsilon_1+\cdots+\upsilon_r=n}} e^{it_1\upsilon_1}\cdots e^{it_r\upsilon_r} \frac{n!}{\upsilon_1!\cdots\upsilon_r!} P_1^{\upsilon_1}\cdots P_r^{\upsilon_r} \\ &= \left(P_1e^{it_1}+\cdots+P_re^{it_r}\right)^n. \end{split}$$

Let's enter new quantities:

$$x_i = \frac{\upsilon_i - np_i}{\sqrt{np_i}}, \quad i = 1, 2, \dots, r.$$

Then obviously, $\sum x_i \sqrt{p_i} = 0$, $\chi_r^2 = \sum_{i=1}^r x_i^2$. We will

find characteristic function of a random vector $x = (x_1, \dots, x_r)$. We have

$$\begin{split} \varphi\left(t_{1},\cdots,t_{r}\right) &= M \mathrm{e}^{i\left(t_{1}x\right)} = M \mathrm{e}^{i\left(t_{1}\frac{\upsilon-np}{\sqrt{np}}\right)} = \sum_{\substack{\upsilon_{1}\geq0\\ \sum\upsilon_{i}=n}} \mathrm{e}^{it_{1}\frac{\upsilon_{1}-np_{1}}{\sqrt{np_{1}}}} \cdots \mathrm{e}^{it_{r}\frac{\upsilon_{r}-np_{r}}{\sqrt{np_{r}}}} \cdot \frac{n!}{\upsilon_{1}!\cdots\upsilon_{r}!} P_{1}^{\upsilon_{1}}\cdots P_{r}^{\upsilon_{r}} \\ &= \mathrm{e}^{-i\sum\iota_{k}\frac{np_{k}}{\sqrt{np_{k}}}} \cdot \sum_{\substack{\upsilon_{1}\geq0\\ \sum\upsilon_{i}=n}} \mathrm{e}^{it_{1}\frac{\upsilon_{1}}{\sqrt{np_{1}}}} \cdots \mathrm{e}^{it_{r}\frac{\upsilon_{r}}{\sqrt{np_{r}}}} \cdot \frac{n!}{\upsilon_{1}!\cdots\upsilon_{r}!} P_{1}^{\upsilon_{1}}\cdots P_{r}^{\upsilon_{r}} = \mathrm{e}^{-i\sqrt{n}\sum\iota_{k}\sqrt{pk}} \left(P_{1}\mathrm{e}^{\frac{i\iota_{1}}{\sqrt{np_{1}}}} + \cdots + P_{r}\mathrm{e}^{\frac{i\iota_{r}}{\sqrt{np_{r}}}}\right) \end{split} \tag{3.4}$$

Further, for any fixed t_1, \dots, t_r^n , we will receive

$$\ln \varphi(t_1, \dots, t_r) = n \ln \left(\sum P_k e^{it_k / \sqrt{np_k}} \right) - i \sqrt{n} \sum t_k \sqrt{p_k}$$
(3.5)

From decompositions $e^x = 1 + x + \frac{x^2}{2!} + O(x^3)$, $\ln(1+x) = x - \frac{x^2}{2!} + \frac{1}{3}R$, $|R| \le |x^3|$, and from (2.5) follows that

$$\sum p_{k} e^{\frac{it_{k}}{\sqrt{np_{k}}}} = \sum p_{k} + \sum p_{k}^{\frac{it_{k}}{\sqrt{np_{k}}}} + \frac{1}{2} \sum p_{k} \frac{(i)^{2} t_{k}^{2}}{\left(\sqrt{np_{k}}\right)^{2}} + O(n^{-3/2}) = \sum p_{k} + \sum p_{k}^{\frac{it_{k}}{\sqrt{np_{k}}}} - \frac{1}{2} \sum \frac{t_{k}^{2}}{n} + O(n^{-3/2}),$$

$$\ln \varphi(t_{1}, \dots, t_{r}) = n \ln \left[1 + \frac{i}{\sqrt{n}} \sum t_{k} \sqrt{p_{k}} - \frac{1}{2n} \sum t_{k}^{2} + O(n^{-3/2}) \right] - i \sqrt{n} \sum t_{k} \sqrt{p_{k}}$$

$$= n \ln \left[\frac{i}{\sqrt{n}} \sum t_{k} \sqrt{p_{k}} - \frac{1}{2n} \sum t_{k}^{2} + O(n^{-3/2}) \right] - \frac{n}{2} \left[-\frac{i}{\sqrt{n}} \sum t_{k} \sqrt{p_{k}} - \frac{1}{2n} \sum t_{k}^{2} + O(n^{-3/2}) \right]^{2} + \frac{n}{3} R - i \sqrt{n} \sum t_{k} \sqrt{p_{k}}$$

$$= -\frac{1}{2} \sum t_{k}^{2} + \frac{1}{2} \left(\sum t_{k} \sqrt{p_{k}} \right)^{2} + O(n^{-1/2})$$

$$(3.6)$$

So, now we can receive that

$$\lim_{\substack{n \to \infty \\ n \to \infty}} \varphi(t_1, \dots, t_r) = e^{-\frac{1}{2} \left[\sum t_k^2 - \left(\sum t_k \sqrt{p_k}\right)^2\right]} = e^{-\frac{1}{2}Q(t_1, \dots, t_r)}$$
(3.7)

The square-law form

$$Q(t_1,\dots,t_r) = \sum_{k} t_k^2 - \left(\sum_{k} t_k \sqrt{p_k}\right)^2$$

has a matrix $\Lambda = I - pp'$ where I designates an individual matrix, and P is a vector—column, replacing t_1, \cdots, t_r with new variables u_1, \cdots, u_r by means of orthogonal transformation, at which $u_r = \sum t_k \sqrt{p_k}$, we will receive

$$Q(t_1,\dots,t_r) = \sum_{1}^{r} t_k^2 - \left(\sum_{1}^{r} t_k^2 \sqrt{p_k}\right)^2 = \sum_{1}^{r} u_k^2 - u_r^2 = \sum_{1}^{r-1} u_r^2.$$

So, the square-law form $Q(t_1,\cdots,t_r)$ is non-negative and also has a rank r-1, *i.e.* at $n\to\infty$, joint characteristic function of quantities x_1,\cdots,x_r aspires to the expression $\exp(-1/2Q)$, which is characteristic function of some nonintrinsic normal distribution of a rank r-1, in which all weight is concentrated to a hyperplane $\sum x_k \sqrt{p_k} = 0$.

From the continuity theorem follows that x_1, \dots, x_r have nonintrinsic normal distribution with zero average and a matrix of the second moments Λ . From here we receive that the quantity $\chi_r^2 = \sum x_k^2$ in a limit has distribution χ^2 with r-1 freedom degrees.

4. Noncentral χ^2 -Distribution

Let's consider that y_1, y_2, \dots, y_n —the independent random variables with normal distribution with an average μ_i ($i = 1, 2, \dots, n$) and a dispersion 1, *i.e.* $y_i \sim N$ ($\mu_i, 1$) ($i = 1, 2, \dots, n$). Then random variable distribution

$$u = \sum_{i=1}^{n} y_i^2$$

is called as noncentral χ^2 -distribution [1-3].

The quantity \sqrt{u} represents radius of a hypersphere in n-dimensional space [1,4].

Random variable distribution u depends only on pa-

rameters n and $\sigma = \left(\sum_{i=1}^{n} \mu_i^2\right)^{1/2}$. Therefore it also names

as noncentral χ^2 -distribution with n degrees of freedom and non-centrality parameter σ [2,5]. In this case, following [4], a random variable u we will designate

$$u=\chi_{n;\sigma}^2$$

If, $\sigma = 0$, *i.e.* $\mu_i = 0$ ($i = 1, 2, \dots, n$), distribution of random variable u named as central χ^2 -distribution or it is simple χ^2 -distribution with n degrees of freedom and

a random variable u we will designate

$$u=\chi_n^2$$
.

Let $P\left\{\chi_n^2\right\}\chi_{\alpha;\sigma}^2\right\} = \alpha$. Quantity $\chi_{\alpha;n}^2\rangle 0$ is named as a threshold or α - percentage point of χ^2 -distribution with n freedom degrees. Its values for various α and n [5]. The mean and variance of a random variable $\chi_{n;\sigma}^2$ are

$$M\left\{\chi_{n;\sigma}^2\right\} = n + \sigma^2; D\left\{\chi_{n;\sigma}^2\right\} = 2n + 4\sigma^2.$$

If $u_1 = \chi^2_{n_1;\sigma_1}$ and $u_2 = \chi^2_{n_2;\sigma_2}$ —independent random variables, then from definition of noncentral χ^2 -distribution it follows that their sum $u = u_1 + u_2 = \chi^2_{n;\sigma}$ has noncentral χ^2 -distribution with $n = n_1 + n_2$ degrees of freedom and parameters of not centrality $\sigma = \left(\sigma_1^2 + \sigma_2^2\right)^{1/2}$.

5. Main Results

For the proof of Q_1 and Q_2 independence we will result following auxiliary statements.

Lemma 5.1. The rank of the sum of square-law forms doesn't surpass the sum of their ranks.

Proof. It is enough to show that if A_1 and A_2 are matrixes of one order and the rank A_i is equal to n_i , then $r(A_1 + A_2) \le r_1 + r_2$. For the vector space generated by columns A_i , we will choose basis from vectors r_i . As columns $A_1 + A_2$ are equal to the sums of corresponding columns A_1 and A_2 , then they are linear combinations $r_1 + r_2$ of vectors of two bases; hence, the number of linearly independent columns in $A_1 + A_2$ can't surpass $r_1 + r_2$. Hence, $r(A_1 + A_2) \le r_1 + r_2$. The lemma is proved.

Consequence. If $\sum_{i=1}^{N} y_i^2 = Q_1 + \dots + Q_s$, where the rank

 Q_j is less or equal to n_j , $j = \overline{1,s}$ and if $n_1 + n_2 + \dots + n_s = N$, then $r(Q_j) = n_j$, $j = \overline{1,s}$.

Proof. It follows directly from a lemma 5.1. On the one hand

$$r\left(\sum_{j=1}^{s} Q_{j}\right) \le \sum_{j=1}^{s} r\left(Q_{j}\right) \le \sum_{j=1}^{s} n_{j} = N$$

and on the other hand

$$r\left(\sum_{j=1}^{s} Q_j\right) = r\left(\sum_{i=1}^{N} y_i^2\right) = N.$$

Hence.

$$\sum_{j=1}^{s} r(Q_j) = N.$$

Under a condition of $r(Q_j) \le n_j$, $j = \overline{1,s}$, performance of last equality is possible only when $r(Q_j) = n_j$,

 $j = \overline{1,s}$, as proves a consequence.

Lemma 5.2. If Q is the square-law form from variables y_1, \dots, y_N and can be expressed as the square-law form from the variables z_1, \dots, z_p which are linear combinations of y_1, \dots, y_N , $\operatorname{To} r(Q) \leq p$. **Proof.** Let $Q = y'A_{N \times N}y = z'B_{p \times p}z$ and $z = C_{p \times N}y$,

Proof. Let $Q = y'A_{N \times N}y = z'B_{p \times p}z$ and $z = C_{p \times N}y$, A and B are symmetric. Then from equality Q = y'C'BCy follows that A = C'BC, and on a lemma 2.1 it is received: $r(Q) = r(A) = r((C'B)C) \le r(C)$. As C - a matrix of the size $(p \times N)$, then $r(C) \le p$. The lemma is proved.

Using resulted above the statement, we will start the proof of independence Q_1 and Q_2 . As

$$Q_0 = y'y - \hat{\beta}^{o'} X^{o'} y$$
, then
 $y'y = Q_1 + Q_2 + Q_3$ (5.1)

where

$$Q_3 = \hat{\beta^{o'}} X^{o'} y = y' A_3 y; \quad A_3 = X^o (X^{o'} X^o)^{-1} X^{o'}.$$

Let's define ranks of square-law forms Q_1 , Q_2 and Q_3 . As $r(A_3) = p_0$, then $r(Q_3) = n_3 = p_0$ [1,2,5]. We will pass to the analysis of the square-law form

$$Q_2 = \sum_{l=1}^{n} \sum_{s=1}^{m_l} (y_{ls} - \overline{y}_l)^2$$
.

Let's enter variables $z_{ls} = y_{ls} - \overline{y}_l$, $l = \overline{1, n}$; $s = \overline{1, m_l}$. It is obvious that

$$Q_2 = \sum_{l=1}^n \sum_{s=1}^{m_l} z_{ls}^2 .$$

As
$$\overline{y}_l = \frac{1}{m_l} \sum_{s=1}^{m_l} y_{ls}$$
, then

$$\sum_{s=1}^{m_l} (y_{ls} - \overline{y}_l) = 0 \Rightarrow \sum_{s=1}^{m_l} z_{ls} = 0,$$

therefore

$$z_{lm_l} = -\sum_{r=1}^{m_l-1} z_{ls}$$
.

Thus.

$$Q_2 = \sum_{l=1}^{n} \sum_{s=1}^{m_l-1} z_{ls}^2 + \sum_{l=1}^{n} z_{lm_l}^2 = \sum_{l=1}^{n} \sum_{s=1}^{m_l-1} z_{ls}^2 + \sum_{l=1}^{n} \left(-\sum_{s=1}^{m_l-1} z_{ls} \right)^2.$$

Apparently from this expression, Q_2 is the squarelaw form from n_2 variables $l = \overline{1, n}$; $s = \overline{1, m_l - 1}$,

$$n_2 = \sum_{l=1}^{n} (m_l - 1) = N - n$$
. As variables z_{ls} are linear

combinations of y_{ls} , and applying a lemma 5.2, we receive

$$r(Q_2) \le n_2 = N - n .$$

Following the similar scheme for Q_1 and applying the lemma 5, we find

$$r(Q_1) \le n_1 = n - p_0 \quad .$$

Really, square-law form Q_1 from variables y_{ls} after some transformations can be written down in a kind $Q_1 = z'Tz$, z - n-dimensional vector, and $r(T) = n - p_0$.

On the basis of a consequence of a lemma 5.1 as $n_1 + n_2 + n_3 = N$, we receive $r(Q_1) = n - p_0$; $r(Q_2) = N - n$; $r(Q_3) = p_0$.

Regarding that random variables $\frac{y_{ls}}{\sigma}$, $l=\overline{1,n}$, $s=\overline{1,m_l}$ are independent and have normal distribution $N\left(\eta_{ls}^*,1\right)$, where $\eta_{ls}^*=\frac{\eta_{ls}}{\sigma}=\frac{\eta_l}{\sigma}$, then transition from equality (4.1) to equality

$$\frac{y'y}{\sigma^2} = \frac{Q_1}{\sigma^2} + \frac{Q_2}{\sigma^2} + \frac{Q_3}{\sigma^2}$$

allows to apply the Kohran theorem. Under this theorem random variables $\frac{Q_1}{\sigma^2}$, $\frac{Q_2}{\sigma^2}$ and $\frac{Q_3}{\sigma^2}$ are independent and have noncentral χ^2 -distributions with $n-p_0$, N-n and p_0 freedom degrees. Thus, independence of Q_1 and Q_2 also is proved.

Remark. Applying the Kohran theorem to calculation of parameter of non-centrality δ_2^2 of the square-law form $\frac{Q_2}{\sigma^2}$, it is easy to be convinced that if the hypothesis H_0 is true or not, then $\delta_2^2 = 0$ *i.e.* the quantity $u_2 = \frac{Q_2}{\sigma^2}$ has central χ^2 -distribution:

$$\delta_{2}^{2} = \frac{1}{\sigma^{2}} \sum_{l=1}^{n} \sum_{s=1}^{m_{l}} (\eta_{ls} - \overline{\eta}_{l})^{2} = \frac{1}{\sigma^{2}} \sum_{l=1}^{n} \sum_{s=1}^{m_{l}} \left(\eta_{l} - \frac{1}{m_{l}} \sum_{s=1}^{m_{l}} \eta_{l} \right)^{2}$$
$$= \frac{1}{\sigma^{2}} \sum_{l=1}^{n} \sum_{s=1}^{m_{l}} (\eta_{l} - \eta_{l})^{2} = 0$$

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