

# **Statistical Invariants in the Least Squares Method**

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## Description of the estimation problem

It's necessary to estimate the unknown vector of parameters  $\vec{\beta}$  on the basis of results of  $n$  measurements  $y_i$  of the model function  $f(x, \vec{\beta})$

$$y_i = f(x_i, \vec{\beta}) + \varepsilon_i, \quad i = 1, \dots, n.$$

The results of the measurements are distorted by the experimental errors  $\varepsilon_i$ . The variations of the experimental errors are described by the covariances  $V_{ij}$

$$V_{ij} = \text{cov}(\varepsilon_i, \varepsilon_j)$$

The model function  $f(x, \vec{\beta})$  is an element of a vector space of dimension  $L$

.

## Interpretation of the estimation process

- The set of the experimental data  $y_i, i = 1, \dots, n$  with covariances  $V_{ij}$  can be interpreted as a system of  $n$  particles with coordinates  $y_i$  ; the interaction between particles is described by the values  $V_{ij}$
- in turn, statistical processing (application of LSM) can be interpreted as a transition  $F$  of the  $n$  – particle system from one state  $(y_i, V_{ij})$  to another one  $(\hat{y}_i, R_{ij})$  :

$$F : (y_i, V_{ij}) \Rightarrow (\hat{y}_i, R_{ij})$$

- we are looking for quantities which are **stay unchanged** at transition

## Definition of a scalar product.

A scalar product in the normalized vector space  $\Omega$  can be defined as follows

$$\langle f_k(\vec{x}) \bullet f_l(\vec{x}) \rangle = \sum_i \sum_j f_k(x_i) (V^{-1})_{ij} f_l(x_j)$$

Such the definition meets all the requirements for the scalar product

- commutativity
- distributivity
- uniformity
- positive definiteness (if  $V$  - positive definite matrix)

## Representation of the model function through the basis functions

If a set of functions  $\varphi_0(x), \dots, \varphi_{L-1}(x)$  form a basis in the space  $\Omega$  then the function  $f(x, \vec{\beta})$  can be represented as a linear combination of these functions

$$f(x, \vec{\beta}) \equiv \sum_{m=0}^{L-1} \gamma_m \varphi_m(x)$$

Using the standard procedure of orthogonalization it's possible to transform the initial basis  $\varphi_0(x), \dots, \varphi_{L-1}(x)$  into the orthogonal one  $\psi_0(x), \dots, \psi_{L-1}(x)$

$$\langle \psi_k(x) \cdot \psi_l(x) \rangle = \delta_{kl}$$

Correspondingly, the model function takes the form

$$f(x, \vec{\beta}) \equiv g(x, \vec{\theta}) = \sum_{m=1}^L \theta_m \psi_m(x)$$

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## Estimation problem after transformation of the basis

After orthogonalization of the basis in the space  $\Omega$  the regression equation can be written as follows

$$y_i = \sum_{m=0}^{L-1} \theta_m \psi_m(x) + \varepsilon_i, \quad i = 1, \dots, n.$$

$$V_{ij} = \text{cov}(\varepsilon_i, \varepsilon_j)$$

where the basis functions  $\psi_0(x), \dots, \psi_{L-1}(x)$  are orthogonal ones,  $\vec{\theta}$  - vector to be estimated.

Thus, the initial estimation problem with an arbitrary model function from the space  $\Omega$  was reduced to the problem with a linear model function.

## The LSM estimate

The LSM estimate  $\hat{\theta}$  with the covariance matrix  $W$  for the linear model function is well known

$$\hat{\theta} = (X^T V^{-1} X)^{-1} X^T V^{-1} \vec{y}$$

$$W = (X^T V^{-1} X)^{-1}$$

where  $X_{ij} = \frac{\partial f(x, \vec{\beta}(\hat{\theta}))}{\partial \theta_i} \bigg|_{x=x_j} = \frac{\partial \left\{ \sum_{m=0}^{L-1} \theta_m \psi_m(x) \right\}}{\partial \theta_i} \bigg|_{x=x_j}$  is the matrix of the sensitivity coefficients.

The covariance matrix of estimated values  $\hat{y}_i = f(x_i, \hat{\beta}(\hat{\theta})) \equiv \sum_{m=0}^{L-1} \hat{\theta}_m \psi_m(x)$  of the model function is given by the following expression

$$R_{ij} = cov(\hat{y}_i, \hat{y}_j) = X W X^T$$

# Representation of the LSM estimate in the orthonormal basis

$$\hat{\vec{\theta}} = X^T V^{-1} \vec{y}$$

$$W = E \quad ( \quad W_{kl} \quad = \quad \sum_{i=1}^n \sum_{j=1}^n \psi_k(x_i) (V^{-1})_{ij} \psi_l(x_j) \quad = \quad \delta_{kl} \quad )$$

$$R = XX^T$$

where

$$X_{ij} = \frac{\partial f(x, \vec{\beta}(\vec{\theta}))}{\partial \theta_i} \bigg|_{x=x_j} = \frac{\partial \left\{ \sum_{m=0}^{L-1} \theta_m \psi_m(x) \right\}}{\partial \theta_i} \bigg|_{x=x_j} = \psi_i(x_j)$$

## Statistical invariants

There are **strict** relationships between the characteristics of the system in original and final states (for **nonlinear** model function the relationships are **approximate**)

$$\sum_i c_i \hat{y}_i = \sum_i c_i y_i \quad \sum_i \sum_j c_i R_{ij} c_j = \sum_i c_i V_{ij} c_j$$

where weights  $c_i$  are determined as follows

$$c_i = \frac{\sum_j (V^{-1})_{ji}}{\sum_k \sum_j (V^{-1})_{jk}}$$

Thus, the evaluated values  $\hat{y}_i$  and their covariances  $R_{ij}$  are result of a **redistribution** of the experimental values  $y_i$  and their covariances  $V_{ij}$ .

The redistribution is managed by the weights  $c_i$ .

## Interpretation of weights

$$c_i = \frac{\sum_j (V^{-1})_{ji}}{\sum_k \sum_j (V^{-1})_{jk}}$$

a share of overall information on  
the uncertainty of the multipoint  
system related to the point *i*

# Interpretation of the statistical invariants

The invariants have a clear statistical interpretation

$$\sum_i c_i \hat{y}_i = \sum_i c_i y_i$$

Average (weighted in special way) value of the model function in the range under consideration

$$\sum_i \sum_j c_i R_{ij} c_j = \sum_i c_i V_{ij} c_j$$

Variance of the average (weighted in special way) value of the model function in the range under consideration

## Side results during the derivation process

Trace of the matrix  $RV^{-1}$  is equal to the dimension  $L$  of the basis  
( = dimension of the vector space  $\Omega$  ) :  $Tr(RV^{-1}) = L$

$$\sum_{i=1}^n (RV^{-1})_{ii} = \sum_{i=1}^n \sum_{j=1}^n R_{ij} (V^{-1})_{ji} =$$

$$= \sum_{i=1}^n \sum_{j=1}^n \left\{ \sum_{k=0}^{L-1} \psi_k(x_i) \psi_k(x_j) \right\} (V^{-1})_{ji} =$$

$$= \sum_{k=0}^{L-1} \left\{ \sum_{i=1}^n \sum_{j=1}^n \psi_k(x_i) (V^{-1})_{ji} \psi_k(x_j) \right\} = \sum_{k=0}^{L-1} \delta_{kk} = L$$

## Useful inequalities for the experimental covariances

$$\frac{\sum_j (V^{-1})_{ji}}{\sum_k \sum_j (V^{-1})_{jk}} \geq 0$$

from positivity of weights

$$\sum_k \sum_j (V^{-1})_{jk} > 0$$

from positivity of variance  
of the physical quantity

## Example 1

$\Omega$  – the space of polynomials of degree lower than  $L$

1. Basis  $\varphi_0(x), \dots, \varphi_{L-1}(x)$ :

$$1, \quad x, \dots, \quad x^{L-1}$$

2. Orthonormal basis  $\psi_0(x), \psi_1(x), \dots, \psi_{L-1}(x)$  is constructed as follows

$$\lambda \psi_j(x) = (x - \alpha_{j-1}) \psi_{j-1}(x) - \alpha_{j-2} \psi_{j-2}(x) - \dots - \alpha_0 \psi_0(x)$$

where coefficients  $\alpha_0, \alpha_1, \dots, \alpha_{j-1}$  are calculated from requirements of orthogonality

$$\langle \psi_j(x) \cdot \psi_k(x) \rangle = 0, \quad k = 1, \dots, j-1$$

or

$$\alpha_k = \frac{\langle x \psi_{j-1}(x) \cdot \psi_k(x) \rangle}{\langle \psi_k(x) \cdot \psi_k(x) \rangle}, \quad k = 1, \dots, j-1$$

## Example 2

$\Omega$  – the space of piece-wise constant functions

$$f(x, \vec{\beta}) = \beta_k \quad \text{if} \quad x \in [x_{i_k}, x_{i_{k+1}}), \quad k = 1, \dots, L$$

1. Basis  $\varphi_0(x), \dots, \varphi_{L-1}(x)$ :

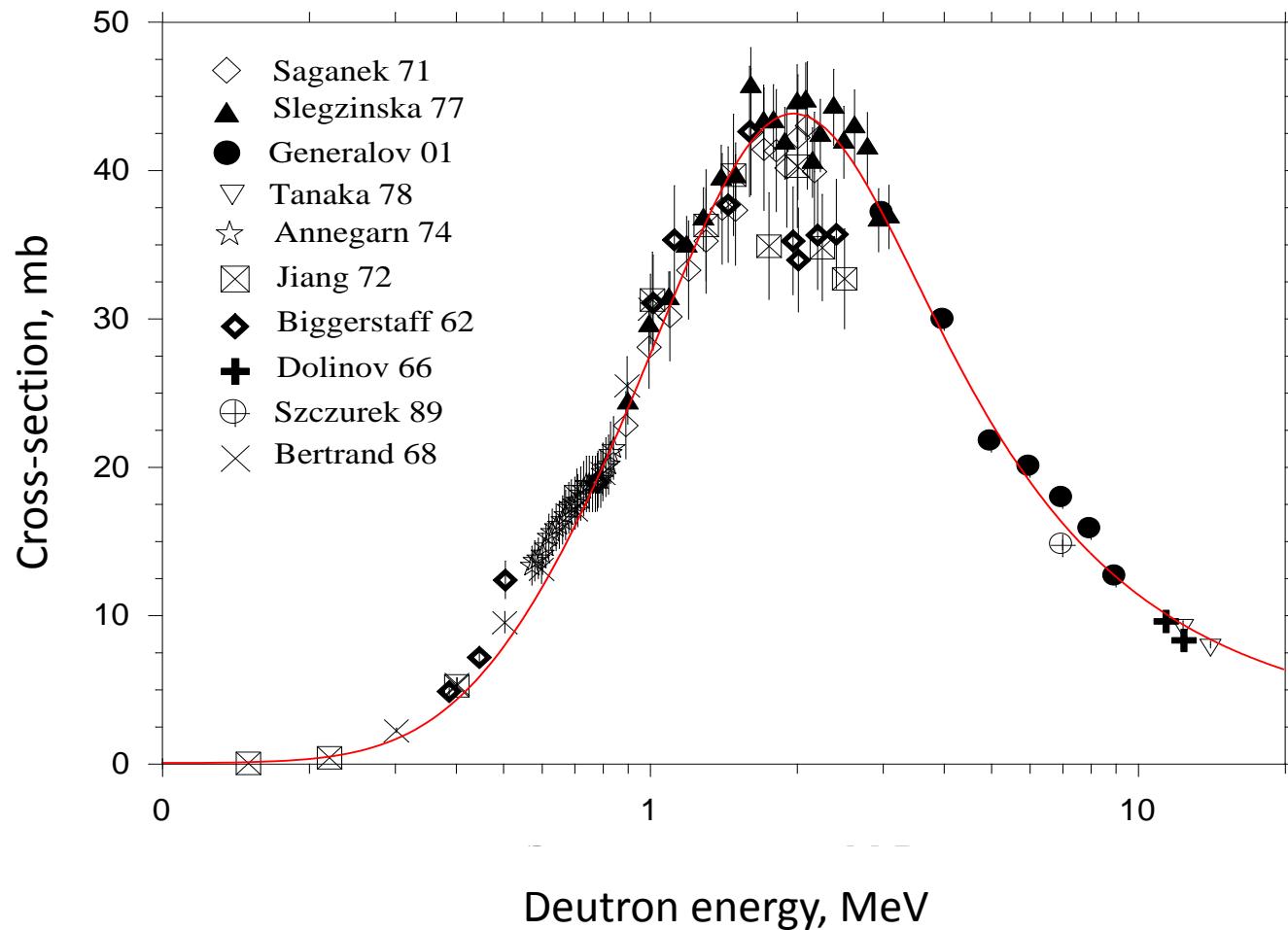
$$\varphi_k(x) = \begin{cases} 1 & \text{if } x \in [x_{i_k}, x_{i_{k+1}}) \\ 0 & \text{if } x \notin [x_{i_k}, x_{i_{k+1}}) \end{cases}$$

## Example 3

$\Omega$  – the space of continuous functions in the range under consideration

- As known any continuous function can be uniformly approximated by a sequence of polynomials
- As already shown for any function from the finite-size polynomial space the statistic invariants are true
- Consequently, it should be expected that for continuous functions the statistic invariants will be approximately true.

# Checking the statistical invariants. Evaluation of the Be9(d, $\alpha$ 0) reaction cross-section



# Evaluation of the ${}^9\text{Be}(\text{d},\alpha\text{0})$ reaction cross-section.

## Checking the statistical invariants

$\sum_i c_i y_i, \text{mb}$	$\sum_i c_i \hat{y}_i, \text{mb}$	$\sum_i \sum_j c_i V_{ij} c_j, \text{mb}^2$	$\sum_i \sum_j c_i R_{ij} c_j, \text{mb}^2$
$0.4548 \cdot 10^{-3}$	$0.4548 \cdot 10^{-3}$	$0.8793 \cdot 10^{-9}$	$0.8793 \cdot 10^{-9}$

## Statistical invariants. Example.

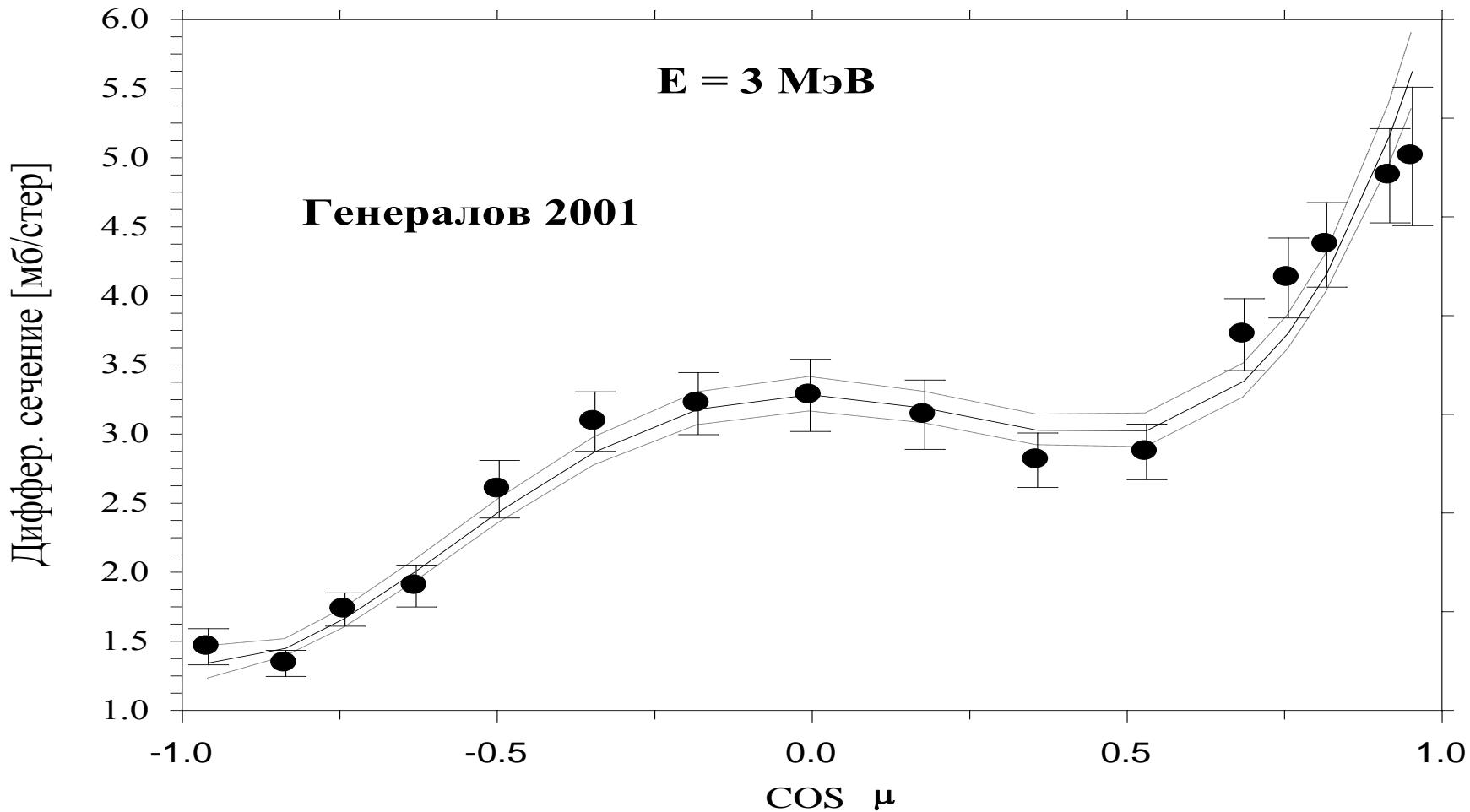
### Evaluation of the ${}^9\text{Be}(\text{d},\alpha\text{0})$ differential reaction cross-section at deuteron energy 3 MeV. Results of measurements [2]

angle, grad	c-section, mb/ster	Uncertainty,%	Angle, grad	c-section, mb/ster	Uncertainty,%
17.7	5.01	10	90.2	3.28	8
23.5	4.87	7	100.4	3.22	7
35.2	4.37	7	110.2	3.09	7
40.9	4.13	7	119.8	2.60	8
46.7	3.72	7	129.0	1.90	8
57.9	2.87	7	137.9	1.73	7
69.0	2.81	7	146.7	1.34	7
79.7	3.14	8	163.5	1.46	9

[2] Generalov L.N. et al., “LI Meeting on Nuclear Spectroscopy and Nuclear Structure”, P. 187. Sarov, RFNC-VNIIEF, 2001 [in Russian], EXFOR F0530

## Statistical invariants. Example.

### Evaluation of the ${}^9\text{Be}(\text{d},\alpha\text{0})$ differential reaction cross-section at deuteron energy 3 MeV. Plot of the experimental data



## Statistical invariants. Example.

### Evaluation of the ${}^9\text{Be}(\text{d},\alpha\text{0})$ differential reaction cross-section.

#### Evaluated coefficients of Legendre polynomial

$$\sigma(\mu, E) = \sum_{l=0}^N \theta_N^l P_l(\mu)$$

$\theta_4^0$	$\theta_4^1$	$\theta_4^2$	$\theta_4^3$	$\theta_4^4$
2.968	1.464	0.01839	1.020	0.8686

## Statistical invariants. Example.

Evaluation of the  ${}^9\text{Be}(\text{d},\alpha\text{0})$  differential reaction cross-section.

Covariances (x1000) of evaluated coefficients of Legendre polynomial

$$\sigma(\mu, E) = \sum_{l=0}^N \theta_N^l P_l(\mu)$$

Number	0	1	2	3	4
$\theta_4^0$	0	3.517			
$\theta_4^1$	1	1.770	7.577		
$\theta_4^2$	2	-1.874	4.912	17.55	
$\theta_4^3$	3	1.238	0.3945	6.929	23.78
$\theta_4^4$	4	2.701	0.1747	-0.7937	10.96
					24.58

# Evaluation of the ${}^9\text{Be}(\text{d},\alpha 0)$ differential reaction cross-section.

## Checking the statistical invariants

$\sum_i c_i y_i, \frac{mb}{ster}$	$\sum_i c_i \hat{y}_i, \frac{mb}{ster}$	$\sum_i \sum_j c_i V_{ij} c_j, \frac{mb^2}{ster^2}$	$\sum_i \sum_j c_i R_{ij} c_j, \frac{mb^2}{ster^2}$
2.260	2.260	2.091-3	2.091-3

## Summary

- Input experimental data (results of measurements and their covariances) **predetermine** the evaluated data and their covariances calculated by the LSM for the model function;
- Weighted sum of elements of the covariance matrix is a natural measure of the integral uncertainty for the random vector.
- As follows from the conservation laws **relative decreasing (increasing) uncertainties** of the evaluated data leads to **pumping** uncertainty information into the off-diagonal covariances
- strict relationships between input experimental data and output evaluated data, restrictions imposed to the covariances of the experimental errors provide verification both the final and intermediate results of calculations

## Some statements of the DDEP methodology “to correct” results of the evaluation

- Uncertainty of the recommended value can not be lower than the most accurate uncertainty of the experimental data
- If contribution of some measurement into statistical sum is larger than 50% than uncertainty of this result of the measurement is expended to get the 50% contribution.