

Bayes Days 2000 at LANL

Three-Day Minicourse on Bayesian Analysis in Physics

Lectures presented by

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Max Planck Institute for Plasma Physics

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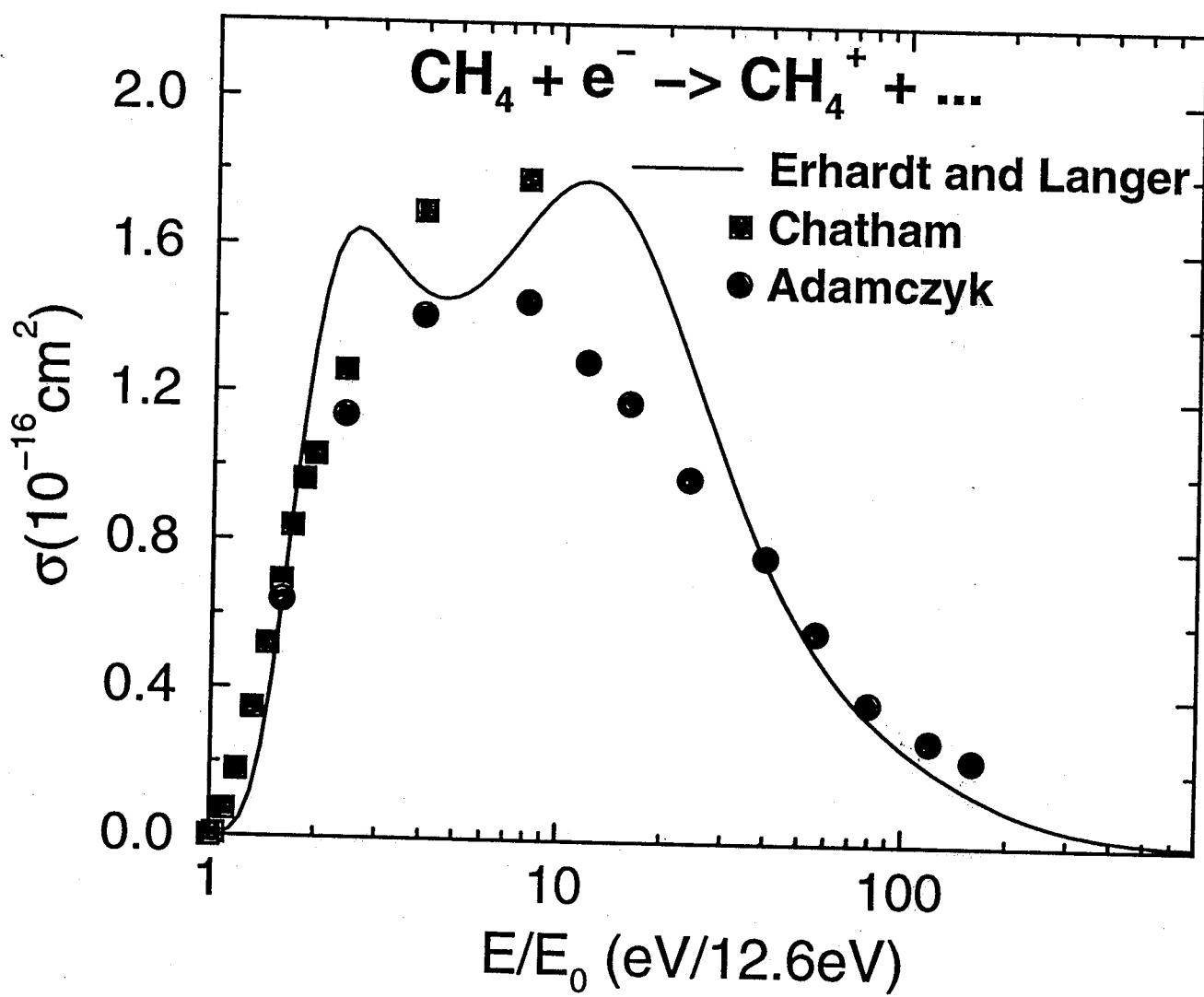
Max-Planck-Institut für Plasmaphysik
Abteilung Oberflächenphysik



Cross sections for partial electron impact ionization of CH₄ and H₂

V. Dose, P. Pecher and R. Preuss

FIGURES



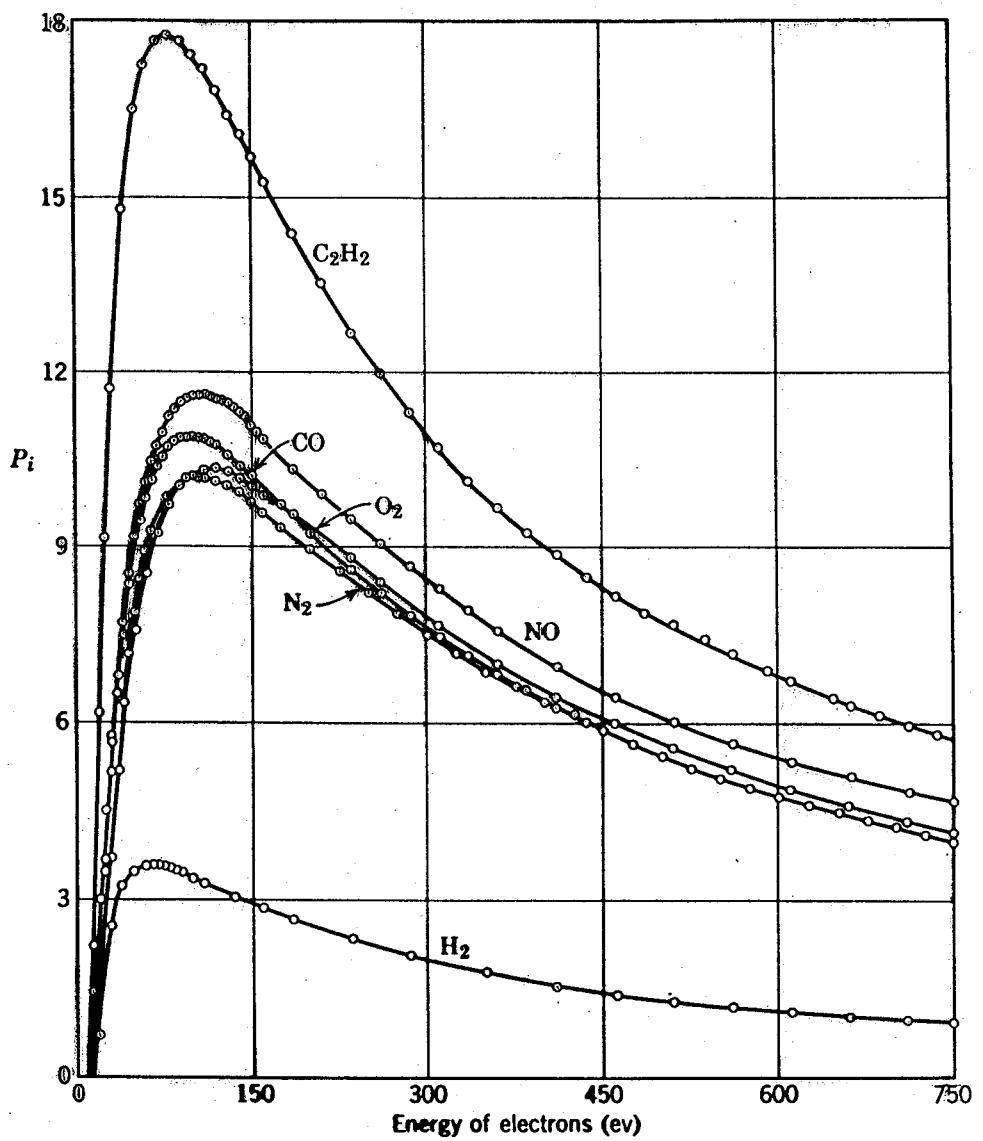
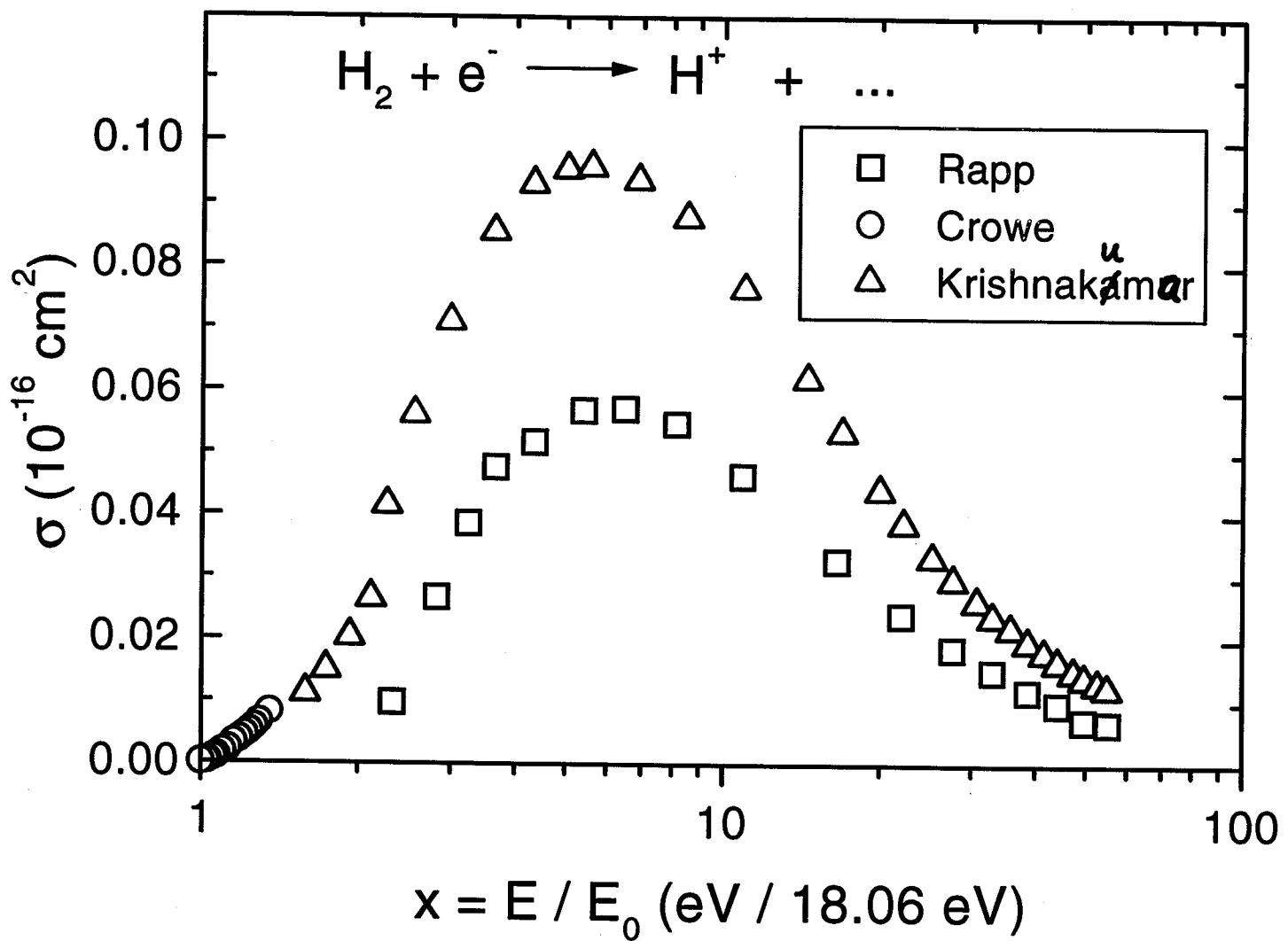


FIG. 5-3-11. The probability of ionization of N_2 , CO , O_2 , NO , H_2 and C_2H_2 . The ordinate represents the number of positive charges per electron per cm path at 1 mm Hg pressure and 0°C. J. T. Tate and P. T. Smith, *Phys. Rev.* **39**, 270 (1932).



unterschiedliche Messbereiche
 verschiedene Absolutkalibrierung

The data

1st set: $\vec{\delta}, \vec{x}, \vec{s}$

2nd set: $\vec{\Delta}, \vec{X}, \vec{S}$

$$p(\vec{\delta}, \vec{\Delta} | \vec{x}, \vec{X}, \vec{s}, \vec{S}, I) = p(\vec{\delta} | \vec{x}, \vec{X}, \vec{s}, \vec{S}, I) \cdot p(\vec{\Delta} | \vec{\delta}, \vec{x}, \vec{X}, \vec{s}, \vec{S}, I)$$

The model

$$\delta_i - c \cdot \varphi(x_i, \vec{\lambda}) = \alpha_i, \quad \langle \alpha_i^2 \rangle = s_i^2$$

$$\gamma \Delta_j - \varphi(X_j, \vec{\lambda}) = \beta_j, \quad \langle \beta_j^2 \rangle = S_j^2$$

$$p(\vec{\delta} | \vec{x}, c, \vec{\lambda}, I) = \prod_i \frac{1}{s_i \sqrt{2\pi}} \exp \left\{ -\frac{1}{2} \left(\frac{\delta_i - c \varphi_i(\vec{\lambda})}{s_i} \right)^2 \right\}$$

$$p(\vec{\Delta} | \vec{X}, c, \vec{\lambda}, \gamma, I) = \prod_j \frac{\gamma}{S_j \sqrt{2\pi}} \exp \left\{ -\frac{1}{2} \left(\frac{\gamma \Delta_j - c \varphi_j(\vec{\lambda})}{S_j} \right)^2 \right\}$$

define:

$$\begin{array}{rcl} \varphi(x_i, \vec{\lambda}) / s_i & = & f_i \\ \delta_i / s_i & = & d_i \end{array} \quad \begin{array}{rcl} \varphi(X_j, \vec{\lambda}) / S_j & = & F_j \\ \Delta_j / S_j & = & D_j \end{array}$$

The likelihood

$$p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, c, \vec{\lambda}, \gamma, I) = \\ (2\pi)^{-n/2} \exp \left\{ -\frac{1}{2} (\vec{d} - c\vec{f})^T (\vec{d} - c\vec{f}) \right\} \cdot \\ (2\pi)^{-N/2} \gamma^N \exp \left\{ -\frac{1}{2} (\gamma\vec{D} - c\vec{F})^T (\gamma\vec{D} - c\vec{F}) \right\}$$

model functions (Born-Bethe)

$$1. \sigma(E) \sim \ln x/x, \quad x = E/E_0 \geq 1$$

$$\varphi(E) = \frac{(x-1)^\epsilon \ln x}{a + (x-1)^\epsilon \cdot x}, \quad \sigma(E) = c \cdot \varphi(E)$$

$$2. \sigma(E) \sim 1/x$$

$$\varphi(E) = \frac{(x-1)^\epsilon}{a + (x-1)^\epsilon \cdot x}, \quad \sigma(E) = c \cdot \varphi(E)$$

Which model applies? What are the numerical values of c and $\vec{\lambda}$?

Bayes' Theorem

$$p(c, \vec{\lambda}, \gamma | \vec{d}, \vec{x}, \vec{D}, \vec{X}, I) = \\ \frac{p(c, \gamma, \vec{\lambda} | I)}{p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, I)} \cdot p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, c, \gamma, \vec{\lambda}, I)$$

$$p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, I) = \int p(\vec{d}, \vec{D}, c, \gamma, \vec{\lambda} | \vec{x}, \vec{X}, I) dc d\gamma d\vec{\lambda} = \\ \int p(c, \gamma, \vec{\lambda} | I) \cdot p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, c, \gamma, \vec{\lambda}, I) dc d\gamma d\vec{\lambda}$$

Priors $(\vec{\lambda} = (a, \epsilon))$

$$p(c, \gamma, \vec{\lambda} | I) = p(c|I)p(\gamma|I)p(a|I)p(\epsilon|I)$$

$$1. \quad c > 0, \quad p(c|I) = 1/c_{\max}$$

$$2. \quad g = \langle \gamma \rangle, \quad p(\gamma|I) = \exp \{-\gamma/g\} / g$$

$$3. \quad a > 0, \quad p(a|I) = 1/a_{\max}$$

$$4. \quad \epsilon > 0, \quad p(\epsilon|I) = \frac{1}{2\sqrt{2\pi}} \exp \left\{ -\frac{1}{2} \left(\frac{\epsilon}{2} \right)^2 \right\}$$

The problem with the global likelihood

$$p(H|D, I) = \frac{p(H|I)}{p(D|I)} \cdot p(D|H, I)$$

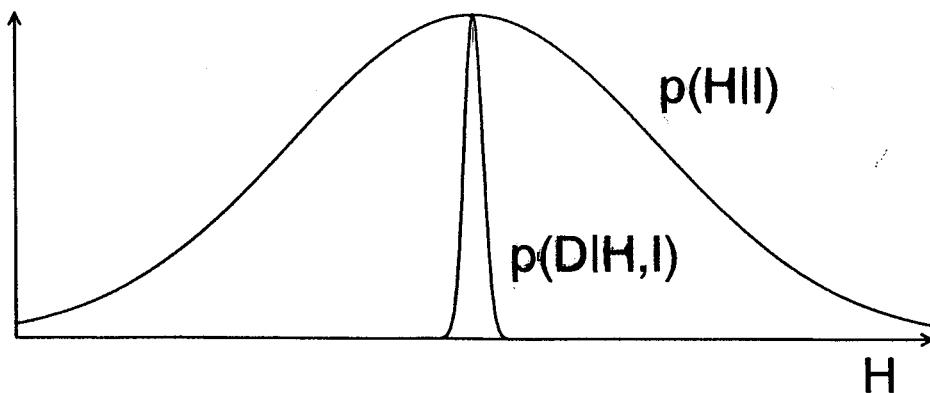
$$\int p(H|I) dH = 1 , \quad \int p(D|H, I) d^E D = 1$$

but

$$\int p(D|H, I) dH = \text{unknown}$$

and may not even be finite.

$$p(D|I) dH = \int \underbrace{p(H|I)}_{\text{sampling density}} p(D|H, I) dH$$



Parameters

$$\langle \xi^n \rangle = \int \xi^n \left\{ \frac{p(c, \gamma, a, \epsilon | I) p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, c, a, \gamma, \epsilon, I)}{p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, I)} \right\} dc d\gamma da d\epsilon$$

Covariances

$$C_{ik} = \langle \xi_i \xi_k \rangle - \langle \xi_i \rangle \langle \xi_k \rangle$$

$$G(\vec{\xi}, \mathbf{C}) = G_0 \exp \left\{ -\frac{1}{2} (\vec{\xi} - \langle \vec{\xi} \rangle)^T \mathbf{C}^{-1} (\vec{\xi} - \langle \vec{\xi} \rangle) \right\}$$

Global likelihood

$$p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, I) =$$

$$\int p(c, \gamma, a, \epsilon | I) p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, c, a, \gamma, \epsilon, I) dc d\gamma da d\epsilon =$$

$$\underbrace{\int G^*(\vec{\xi}, \mathbf{C}^{-1})}_{\text{Sampling density}} \underbrace{\left\{ \frac{p(c, \gamma, a, \epsilon | I) p(\vec{d}, \vec{D} | \vec{x}, \vec{X}, c, \gamma, a, \epsilon, I)}{G^*(\vec{\xi}, \mathbf{C}^{-1})} \right\}}_{\text{integrand, slowly varying}} dc d\gamma da d\epsilon$$

Sampling density integrand, slowly varying

Channel	$M(25a)/M(25b)$	c	a	ε	E_0/eV
$\text{CH}_4 + e^- \rightarrow \text{CH}_4^+ + \dots$	$2 \cdot 10^3 : 1$	9.7	4.4	0.14	12.6
$\text{CH}_4 + e^- \rightarrow \text{CH}_3^+ + \dots$	$10^3 : 1$	6.7	3.5	0.20	14.3
$\text{CH}_4 + e^- \rightarrow \text{CH}_2^+ + \dots$	$10^4 : 1$	0.93	4.0	1.0	15.1
$\text{CH}_4 + e^- \rightarrow \text{CH}^+ + \dots$	$26 : 1$	0.31	0.67	1.7	22.2
$\text{CH}_4 + e^- \rightarrow \text{C}^+ + \dots$	$1 : 2 \cdot 10^2$	0.22	8.7	1.2	25.0
$\text{CH}_4 + e^- \rightarrow \text{H}^+ + \dots$	$1 : 3 \cdot 10^4$	1.3	22	1.2	18.1
$\text{H}_2 + e^- \rightarrow \text{H}_2^+ + \dots$	$10^{10} : 1$	3.9	1.8	0.18	15.43
$\text{H}_2 + e^- \rightarrow \text{H}^+ + \dots$	$1 : 10^{27}$	0.91	34	1.5	18.06

TABLE I. Posterior estimates for the model parameters in Eqn. (25a,b).

Posterior cross sections

$$\langle \sigma^k(z) \rangle = \int \sigma^k p(\sigma|z, \vec{d}, \vec{D}, \vec{x}, \vec{X}, I) d\sigma$$

$$p(\sigma|z, \vec{d}, \vec{D}, \vec{x}, \vec{X}, I) = \\ \int p(\sigma, c, \gamma, a, \epsilon|z, \vec{d}, \vec{D}, \vec{x}, \vec{X}, I) dc d\gamma da d\epsilon = \\ \int p(c, \gamma, a, \epsilon|z, \vec{d}, \vec{D}, \vec{x}, \vec{X}, I) \cdot p(\sigma|z, c, \gamma, a, \epsilon, \vec{d}, \vec{D}, \vec{x}, \vec{X}, I) \\ dc d\gamma da d\epsilon$$

$$p(c, \gamma, a, \epsilon|\vec{d}, \vec{D}, \vec{x}, \vec{X}, I) = \\ \frac{p(c, \gamma, a, \epsilon|I) p(\vec{d}, \vec{D}|\vec{x}, \vec{X}, c, \gamma, a, \epsilon, I)}{p(\vec{d}, \vec{D}|\vec{x}, \vec{X}, I)}$$

sampling density as for parameter estimation

$$p(\sigma|z, c, \gamma, a, \epsilon, \vec{d}, \vec{D}, \vec{x}, \vec{X}, I) = p(\sigma|z, c, a, \epsilon)$$

$$p(\sigma|z, c, \gamma, a, \epsilon) = \delta(\sigma - c\varphi(z, a, \epsilon))$$

$$\langle \sigma^k(z) \rangle = \int \{c\varphi(z, a, \epsilon)\}^k p(c, \gamma, a, \epsilon|\vec{d}, \vec{D}, \vec{x}, \vec{X}, I) dx d\gamma da d\epsilon$$

$$\langle \sigma(z) \rangle, \langle \Delta\sigma^2(z) \rangle$$

