

In the name of God

## COMPUTATIONAL PHYSICS AND NUMERICAL ANALYSIS

## First midterm exam

(Time allowed: 3 hours)

## Theoretical part:

## 1. Widely-used commands in terminal:

**A:** What is the command to connect a cluster? (assume that the valid IP is 192.168.220.100) (2 points)**B:** What is the command to copy a file from cluster to our local computer? (assume that the valid IP is 192.168.220.100) (2 points)**C:** What is the command to make a script as an executable file? (1 points)

## 2. Binomial PDF:

**A:** Prove that the variance of a binomial probability is

$$\sigma^2 = Np(1 - p)$$

(5 points)

**B** Considering the result proved in Part A, now prove that for small  $P(x)$ , the error of the probability density function becomes

$$\sigma_m = \frac{1}{Nh},$$

where,  $h$  is the bin width. (5 points)

## 3. The concept of Probability Density Function (PDF):

Suppose that

$$\bar{\rho}(x) \equiv \left\langle \frac{1}{h} K \left( \frac{x-y}{h} \right) \right\rangle_y = \int_{-\infty}^{\infty} \frac{1}{h} K \left( \frac{x-y}{h} \right) \rho(y) dy$$

Where  $K$  is a kernel such that  $K(A) = 1$  for  $|A| \leq \frac{1}{2}$ , and  $K(A) = 0$  otherwise. Also we define

$$\text{Bias}[\bar{\rho}(x)] \equiv \rho(x) - \bar{\rho}(x)$$

**A:** What is the result of the following limit:

$$\lim_{h \rightarrow 0} \text{Bias}[\bar{\rho}(x)] = ?$$

explain your result. (5 points)

**B:** Using the changing of variable as  $s = \frac{y-x}{h}$  and by Tylor expansion of  $\rho(x + sh)$  up to  $\mathcal{O}(h^3)$ , compute  $\bar{\rho}(x)$ . Finally, determine  $\lim_{h \rightarrow 0} \text{Bias}(\bar{\rho}(x))$ . (5 points)**C:** Let's define  $L$  as

$$L \equiv \text{Var}(\bar{\rho}(x)) + (\text{Bias}[\bar{\rho}(x)])^2$$

Where  $\text{Var}(\bar{\rho}(x))$  and  $\text{Bias}[\bar{\rho}(x)]$  which have been obtained in part B of question 2 and and part B, respectively. Find the best value of  $h$  by minimizing the  $L$ . (5 points)

## 4. The concept of Correlation:

**A:** Explain different categories of correlation. (5 points)**B:** We have recorded two sets of data,  $\{x\}$  and  $\{y\}$  in an experimental set up. We imagine that the

statistical relation of two mentioned series is given by  $y \triangleq ax + b$ . Now we define an estimator for error as  $\epsilon \equiv \langle (y - (ax + b))^2 \rangle$ . By minimizing the  $\epsilon$ , try to find the statistical meaning of  $CoV \equiv \langle (x - \langle x \rangle)(y - \langle y \rangle) \rangle$ . (5 points)

5. Moments and Cumulants: For a Gaussian distribution of random variable,  $x$ , with variance equates to  $\sigma^2$ , we use the mapping  $x \rightarrow y = x - \langle x \rangle$ . Show that  $\mathcal{K}_1$  and  $\mathcal{K}_3$  for  $y$  are zero. What is the second cumulant? (5 points)

**Computational part:**

6. Fitting algorithm. According to the data set provided for you, there are 10 pairs, each pair  $(\bar{x}_i, \bar{y}_i)$  is subject to asymmetric errors (see Figure 1). The error-bars for each point as represented by  $\bar{x}_i \frac{\sigma_x^+}{\sigma_x^-}$  and  $\bar{y}_i \frac{\sigma_y^+}{\sigma_y^-}$ , are  $\sigma_x^- = 0.5, \sigma_x^+ = 5, \sigma_y^- = 2, \sigma_y^+ = 5$ .

**A:** To map our fitting problem with the asymmetric error-bars to a simple case such that the abundance of data points for  $x$  around corresponding mean value, namely  $\bar{x}_i$  and similarly for  $\bar{y}_i$  are constant on different boundary, do following tasks:

- 1) For each pair,  $(\bar{x}_i, \bar{y}_i)$ , generate some data points randomly for the range of  $x_j^{(i)} \in [\bar{x}_i - \sigma_x^-, \bar{x}_i + \sigma_x^+]$  for  $j = 1, \dots, 20$  with constant PDF. (10 points)
- 2) Do the same task as the part 1 just for  $\bar{y}_i$ . (10 points)
- 3) Now, for each  $i$ , collect the pairs as  $(x_j^{(i)}, y_j^{(i)})$ . where  $i = 1, \dots, 10$  and  $j = 1, \dots, 20$ . Finally you have new data set with  $(x_k, y_k)$ , where  $k = 1, \dots, 10 \times 20$  and write them in a text file. (5 points)

**B:** Now by this new data set in your hand, and considering a linear line as theoretical prediction,  $Y_{theo.} = ax + b$  with two free parameters, compute the  $a_{best}$  and  $b_{best}$ . (15 points)

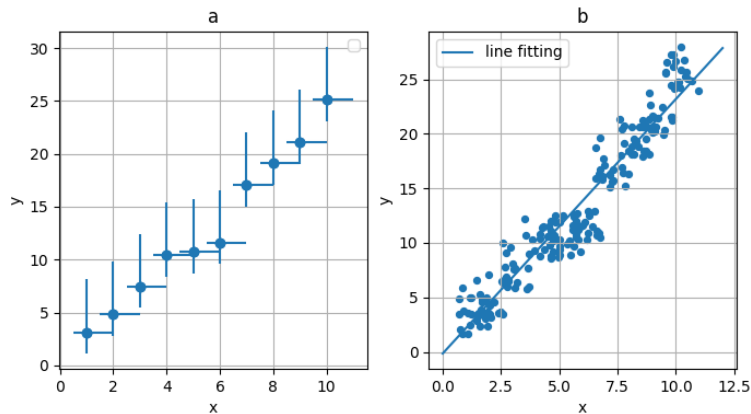


Figure 1: The asymmetric data sets around each filled circle symbols.

Good luck, Movahed

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## Answer Key for First midterm

Numerical Analysis 1403. and Advanced Computational  
Physics

① Commands

5 Points

Ⓐ ssh user@192.168.220.100

Ⓑ scp user@192.168.220.100:/address/



It means here

Ⓒ chmod 0+x  
g+x  
u+x filename.sh

② Binomial PDF

Ⓐ 
$$P(n) = \binom{N}{n} p^n (1-p)^{N-n}$$

$$\langle n \rangle = \sum_{n=0}^N n \binom{N}{n} p^n (1-p)^{N-n}$$

$$= Np$$

$$\sigma^2 = \langle (n - \langle n \rangle)^2 \rangle = \sum_{n=0}^N (n - \langle n \rangle)^2 \binom{N}{n} p^n (1-p)^{N-n}$$

$$\sigma^2 = pN(N-1) + Np - p^2N^2$$

5 points

$$= \cancel{p^2 N^2} - p^2 N + Np - \cancel{p^2 N^2}$$

$$= Np - Np^2 = Np(1-p)$$

(B) 
$$\underline{P(x)} = \lim_{N \rightarrow \infty} \frac{n(x)}{N}$$

$$\frac{dP(x)}{dx} = p(x) : \text{PDF} \quad \text{or} \quad \frac{\Delta P(x)}{\Delta x} = p(x)$$

$$\sigma_{P(x)}^2 = \left( \frac{\sigma_{\Delta P(x)}}{\Delta x} \right)^2 = \frac{Np(1-p)}{N^2 (\Delta x)^2}$$

$$\sigma_m^2 = \frac{\sigma_{P(x)}^2}{\langle n(x) \rangle} = \frac{Np(x)(1-p(x))}{N^2 \Delta x^2 Np(x)} = \frac{(1-p(x))}{N^2 \Delta x^2}$$

5-Points

$$\sigma_m = \frac{1}{N \Delta x}$$

or

$$\sigma_m = \frac{1}{Nh}$$

(3)

(A)

$$\bar{f}(x) = \left\langle \frac{1}{h} K\left(\frac{x-y}{h}\right) \right\rangle_y = \int dy \frac{K\left(\frac{x-y}{h}\right)}{h} f(y)$$

$$\text{Bias}[\bar{f}(x)] \equiv f(x) - \bar{f}(x)$$

$$\lim_{h \rightarrow 0} \text{Bias} = f(x) - \lim_{h \rightarrow 0} \int dy \left( \frac{K\left(\frac{x-y}{h}\right)}{h} \right) f$$

$$\lim_{h \rightarrow 0} \frac{K\left(\frac{x-y}{h}\right)}{h} = \delta_D(x-y) \quad \text{looks like Dirac Delta function}$$

$$\lim_{h \rightarrow 0} \text{Bias}(\bar{f}(x)) = f(x) - \int dy \delta_D(x-y) f(y) = f(x) - f(x) = 0$$

In this case the Kernel include only those values

equates to x and therefore our Bias corresponds to

$f(x)$  itself.

5 points

$$\textcircled{B} \quad s \equiv \frac{x-y}{h} \rightarrow sh = x-y \Rightarrow y = x-sh \quad \boxed{dy = -h ds}$$

$$f(y) = f(x-sh) = f(x) - sh \left. \frac{df}{dx} \right|_{h=0}$$

$$+ \frac{(sh)^2}{2!} \left. \frac{d^2 f}{dx^2} \right|_{h=0} + \underbrace{\mathcal{O}(sh^3)}_{\text{or } \mathcal{O}(h^3)}$$

Therefore

$$\bar{f}(x) = \left\langle \frac{1}{h} K\left(\frac{x-y}{h}\right) \right\rangle_y = \int dy \frac{K\left(\frac{x-y}{h}\right)}{h} \times \left[ f(x) \right.$$

$$\left. - sh \left. \frac{df}{dx} \right|_{h=0} + \frac{(sh)^2}{2!} \left. \frac{d^2 f}{dx^2} \right|_{h=0} + \mathcal{O}(h^3) \right]$$



$$\bar{f}(x) = \int (-h ds) \frac{K(s)}{h} f(x) + \int (-h ds) \frac{K(s)}{h} (-sh) f'(x) \\ + \int (-h ds) \frac{K(s)}{h} \frac{(-sh)^2}{2!} f''(x) + \mathcal{O}(h^3)$$

$$= -f(x) + h f'(x) \int ds s K(s) - \frac{h^2 f''(x)}{2!} \int ds s^2 K(s) + \mathcal{O}(h^3)$$

↑ odd
↓ even

$$\int_{-1/2}^{+1/2} ds s^2 = \frac{s^3}{3} \Big|_{-1/2}^{+1/2} = \frac{1}{12}$$

$$\bar{f}(x) = - \left[ f(x) + \frac{h^2 f''(x)}{2!} \frac{1}{12} \right]$$

$$\lim_{h \rightarrow 0} \text{Bias} = f(x) - (-f(x)) = 2f(x)$$

5-Points

$$\textcircled{C} \quad L = \text{Var}(\bar{f}(x)) + (\text{Bias}[\bar{f}(x)])^2$$

$$= \sigma_m^2 + (\text{Bias}[\bar{f}(x)])^2$$

$$L = \frac{1}{N h^2} + \left( f(x) - \left( -f(x) - \frac{h^2 f''(x)}{24} \right) \right)^2$$

$$0 = \frac{dL}{dh} \Big|_{h=h_{\text{Best}}} = \checkmark$$

5-Points

4) A: ☆ Value  $\left\{ \begin{array}{l} \text{Coefficient} \\ \text{Function} \end{array} \right.$

☆ Type  $\left\{ \begin{array}{l} \text{Linear} \\ \text{Non-Linear} \end{array} \right.$

☆ Relation  $\left\{ \begin{array}{l} \text{Auto-Correlation} \\ \text{Cross-Correlation} \end{array} \right.$

☆ Statistics  $\left\{ \begin{array}{l} \text{Two-Point} \\ \text{n-Point} \end{array} \right.$

☆ Kind  $\left\{ \begin{array}{l} \text{Weighted} \\ \text{Un-Weighted} \end{array} \right.$

5-Points

B) 
$$E = \langle (y - (ax + b))^2 \rangle = \langle y^2 + a^2 x^2 + b^2 + abx - 2axy - 2yb \rangle$$

$$\left. \begin{array}{l} \frac{\partial E}{\partial a} = 0 \rightarrow 2a \langle x^2 \rangle + 2b \langle x \rangle - 2 \langle xy \rangle = 0 \\ \frac{\partial E}{\partial b} = 0 \rightarrow 2b + 2a \langle x \rangle - 2 \langle y \rangle = 0 \end{array} \right\} \rightarrow \boxed{b = \langle y \rangle - a \langle x \rangle}$$

$$a = \frac{\langle xy \rangle - \langle x \rangle \langle y \rangle}{\langle x^2 \rangle - \langle x \rangle^2} \triangleq \text{Cov}$$

5-Points

5)

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x - \langle x \rangle)^2}{2\sigma^2}}$$

$$y = x - \langle x \rangle \rightarrow p(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{y^2}{2\sigma^2}}$$

$$K_1 = M_1 = \langle y \rangle = \langle x - \langle x \rangle \rangle = \langle x \rangle - \langle x \rangle = 0$$

$$\begin{aligned} K_3 &= M_3 - 3M_1M_2 + 2M_1^3 \\ &= M_3 = \langle y^3 \rangle = \int dy \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{y^2}{2\sigma^2}} y^3 = 0 \end{aligned}$$

$$K_2 = M_2 - M_1^2 = M_2 - K_1^2 = M_2 = \sigma^2$$

5-points

6) Non-linear Langevin Eq.

$$\frac{dv}{dt} = \underbrace{\gamma(t, v)}_{\text{Deterministic Part}} + \underbrace{\eta(t)}_{\text{Stochastic Part}}$$



$$\langle \eta(t) \rangle = 0$$

$$P(\eta(t)) = \mathcal{N}(0, \sigma_\eta^2)$$

$$\langle \eta(t) \eta(t') \rangle = \sigma_\eta^2 \delta_0(t-t')$$

10 - Points

### Computational Part

(A) Use Random Generator to generate

Data for each point with center  $\bar{x}_i$  and  $\bar{y}_i$ .

$$x_j^{(i)} = a + R(b-a) = (\bar{x}_i - \sigma_x^-) + R[\sigma_x^+ - \sigma_x^-]$$

$$y_j^{(i)} = (\bar{y}_i - \sigma_y^-) + R'[\sigma_y^+ - \sigma_y^-]$$

$R$  and  $R'$  are Random Number with

Flat Probability Distribution

(B)

$$Y_{\text{theo}} = ax + b$$

$$X^2 = \sum_{k=1}^{200} [y_k - (ax_k + b)]^2$$

$$\frac{\partial X^2}{\partial a} = 0$$

and

$$\frac{\partial X^2}{\partial b} = 0$$

$$a = \frac{\sum_{k=1}^N (x_k - \bar{x}) y_k}{\sum_{k=1}^N (x_k - \bar{x})^2}$$

$$\bar{x} = \frac{1}{N} \sum_{k=1}^N x_k$$

$$b = \frac{1}{N} \sum_{k=1}^N y_k - a \frac{1}{N} \sum_{k=1}^N x_k$$

$$a \simeq 2.37$$

$$b \simeq 2.47 \times 10^{-2}$$