

Assignment 1: CS 215

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Contents

Question 1

1. $Y_1 = \max(X_1, X_2, \dots, X_n)$
 $P(Y_1 \leq y) = P(X_1 \leq y) \times \dots \times P(X_n \leq y)$
Since X_1, X_2, \dots, X_n are independent
 $\therefore F_{Y_1}(y) = \prod F_{X_i}(y) = [F_X(y)]^n$
Since they are identical
 $\therefore F_{Y_1}(y) = [F_X(y)]^n$
 $f_{Y_1}(y) = \frac{d}{dy} [F_X(y)]^n = n [F_X(y)]^{n-1} f_X(y)$
 \therefore cdf of $Y_1 = [F_X(y)]^n$
pdf of $Y_1 = n f_X(y) [F_X(y)]^{n-1}$

$Y_2 = \min(X_1, X_2, \dots, X_n)$
 $P(Y_2 \leq y) = P(Y_2 \geq y) = P(X_1 \geq y) P(X_2 \geq y) \dots P(X_n \geq y)$
 $P(Y_2 \geq y) = [1 - F_X(y)]^n$
 $\therefore 1 - F_{Y_2}(y) = [1 - F_X(y)]^n$
 $F_{Y_2}(y) = 1 - [1 - F_X(y)]^n$
 $f_{Y_2}(y) = n [1 - F_X(y)]^{n-1} f_X(y)$
 \therefore cdf of $Y_2 = 1 - [1 - F_X(y)]^n$
pdf of $Y_2 = n f_X(y) [1 - F_X(y)]^{n-1}$

Question 2

Question 3

3. Consider $Y = X - \mu$
 $E[Y] = 0$ $E[\text{Var}(Y)] = \sigma^2$

$\therefore P(Y \geq \tau)$ for $\tau > 0$
 $P(Y \geq \tau) \leq P((Y+b)^2 \geq (\tau+b)^2)$ for $b \geq 0$
 as it will be cover both types of values

\therefore Applying Markov's inequality
 $P((Y+b)^2 \geq (\tau+b)^2) \leq \frac{E[(Y+b)^2]}{(\tau+b)^2} \leq \frac{\sigma^2 + b^2}{(\tau+b)^2}$

$\therefore P(X - \mu \geq \tau) \leq \frac{\sigma^2 + b^2}{(\tau+b)^2}$ for $b \geq 0$

Now differentiate $\frac{\sigma^2 + b^2}{(\tau+b)^2}$ and equate to 0

$\frac{d}{db} \left(\frac{\sigma^2 + b^2}{(\tau+b)^2} \right) = \frac{2b(\tau+b)^2 - (\sigma^2 + b^2)2(\tau+b)}{(\tau+b)^4}$
 $b\tau + b^2 = \sigma^2 + b^2 \Rightarrow b = \sigma^2/\tau$ so for this b, exp. is min

$\therefore P(X - \mu \geq \tau) \leq \frac{\sigma^2 + \sigma^4/\tau^2}{(\tau + \sigma^2/\tau)^2} = \frac{\sigma^2(1 + \sigma^2/\tau^2)}{(1 + \sigma^2/\tau^2)^2}$

$\frac{\sigma^2 + \sigma^4/\tau^2}{(\tau^2 + \sigma^2)^2/\tau^2} = \frac{\sigma^2\tau^2 + \sigma^4}{(\tau^2 + \sigma^2)^2} = \frac{\sigma^2}{\tau^2 + \sigma^2}$

$\therefore P(X - \mu \geq \tau) \leq \frac{\sigma^2}{\tau^2 + \sigma^2}$

∴ for any random variable and $\tau > 0$

$$P(X - \mu \geq \tau) \leq \frac{\sigma^2}{\sigma^2 + \tau^2}$$

Now consider $\tau < 0$ and $b = -\tau$

let say $Y = -X$ (with mean $-\mu$ and variance σ)

$$\therefore P(Y + \mu \geq b) \leq \frac{\sigma^2}{\sigma^2 + \tau^2} \text{ as } b^2 = \tau^2$$

$$P(-X + \mu \geq b) \leq \frac{\sigma^2}{\sigma^2 + \tau^2}$$

$$\therefore P(X \leq \mu - b) \leq \frac{\sigma^2}{\sigma^2 + \tau^2}$$

$$P(X \leq \mu + \tau) \leq \frac{\sigma^2}{\sigma^2 + \tau^2}$$

$$-P(X \leq \mu + \tau) \geq -\frac{\sigma^2}{\sigma^2 + \tau^2}$$

$$1 - P(X \leq \mu + \tau) \geq 1 - \frac{\sigma^2}{\sigma^2 + \tau^2}$$

$$\therefore P(X \geq \mu + \tau) \geq 1 - \frac{\sigma^2}{\sigma^2 + \tau^2}$$

$$\text{Thus for } \tau < 0, P(X \geq \mu + \tau) \geq 1 - \frac{\sigma^2}{\sigma^2 + \tau^2}$$

Question 4

4. For $t \geq 0$
For $t > 0$

$$\phi_X(t) = E[e^{Xt}]$$

$$= \sum_{i=1}^n e^{x_i t} (P(X=x_i)) \quad \text{for discrete}$$

$$= \int_{-\infty}^{\infty} e^{xt} f_X(x) dx \quad \text{for continuous}$$

First prove for continuous,

$$\phi_X(t) = \int_{-\infty}^{\infty} e^{xt} f_X(x) dx$$

if $t > 0$, $e^{x_1 t} > e^{x_2 t}$ if $x_1 > x_2$

$$\phi_X(t) \geq \int_{x_0}^{\infty} e^{xt} f_X(x) dx \geq \int_{x_0}^{\infty} e^{x_0 t} f_X(x) dx \quad [\text{if } t > 0]$$

$$\therefore \phi_X(t) \geq e^{x_0 t} \int_{x_0}^{\infty} f_X(x) dx = e^{x_0 t} (P(X \geq x_0))$$

$$\therefore \frac{P(X \geq x_0)}{P(X \geq x_0)} \leq e^{-x_0 t} \phi_X(t)$$

Now for discrete,

$$\phi_X(t) = \sum_{i=1}^n e^{x_i t} P(X=x_i)$$

if $t > 0$

$$\phi_X(t) \geq \sum_i e^{x_0 t} P(X=x_i) \quad \text{here } x_i \geq x_0$$

$$\phi_X(t) \geq e^{x_0 t} \sum_i P(X=x_i) \quad \text{where } x_i \geq x_0$$

$$\therefore \phi_X(t) \geq e^{x_0 t} P(X \geq x_0)$$

$$\therefore P(X \geq x_0) \leq e^{-x_0 t} \phi_X(t)$$

For $t < 0$

For continuous,

$$\phi_X(t) = \int_{-\infty}^{\infty} e^{+tx} f_X(x) dx \geq \int_{-\infty}^{x_0} e^{+tx} f_X(x) dx$$

if $t < 0$, $e^{+tx_1} > e^{+tx_2}$ if $x_1 < x_2$

$$\therefore \phi_X(t) \geq \int_{-\infty}^{x_0} e^{tx} f_X(x) dx \geq \int_{-\infty}^{x_0} e^{x_0 t} f_X(x) dx$$

$$\therefore \phi_X(t) \geq e^{tx_0} P(X \leq x_0)$$

$$\therefore P(X \leq x_0) \leq e^{-tx_0} \phi_X(t)$$

For discrete,

$$\phi_X(t) = \sum_{i=1}^n e^{x_i t} P(X=x_i)$$

$$\phi_X(t) \geq \sum_j e^{x_0 t} P(X=x_j) \quad \text{where } x_j \leq x_0$$

because if $t < 0$, $e^{x_0 t} \leq e^{x_j t}$

$$\phi_X(t) \geq e^{x_0 t} P(X \leq x_0)$$

$$\therefore P(X \leq x_0) \leq e^{-tx_0} \phi_X(t)$$

Now for the second part

$$\phi_{x_i}(t) \leq 1 - p_i + p_i e^t = 1 + p_i(e^t - 1) \leq e^{p_i(e^t - 1)}$$

Therefore

$$\phi_x(t) = \prod_{i=1}^n \phi_{x_i}(t) \leq \prod_{i=1}^n e^{p_i(e^t - 1)} = e^{\sum_{i=1}^n p_i(e^t - 1)} = e^{\mu(e^t - 1)} \quad \text{as } \sum p_i = \mu$$

\therefore Using the first inequality for $t > 0$, as for $t = 0$

$$P(X > (1+s)\mu) \leq 1 \text{ which is obviously true,}$$

$$P(X > (1+s)\mu) \leq e^{-t(1+s)\mu} \phi_x(t) \leq e^{-t(1+s)\mu} e^{\mu(e^t - 1)}$$

$$\therefore P(X > (1+s)\mu) \leq \frac{e^{\mu(e^t - 1)}}{e^{(1+s)\mu t}}$$

Now we want to minimize $e^{\mu(e^t - 1) - (1+s)\mu t}$ with respect to t .

So we have to minimize $\mu(e^t - 1) - (1+s)\mu t$

Taking derivative and equating to 0

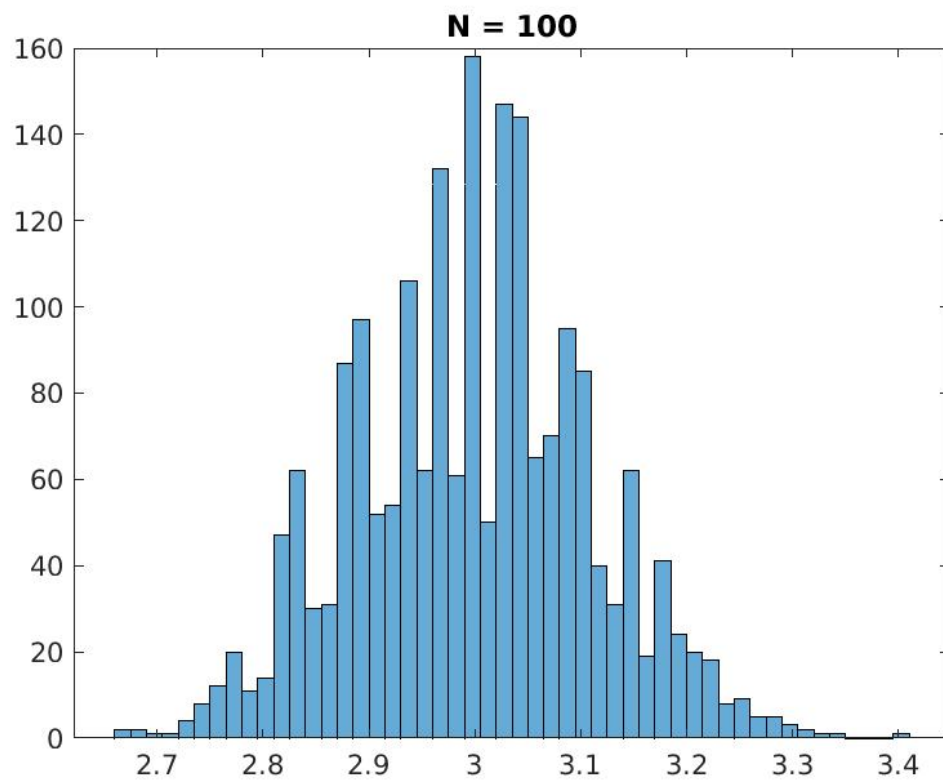
$$\mu e^t = \mu(1+s)$$

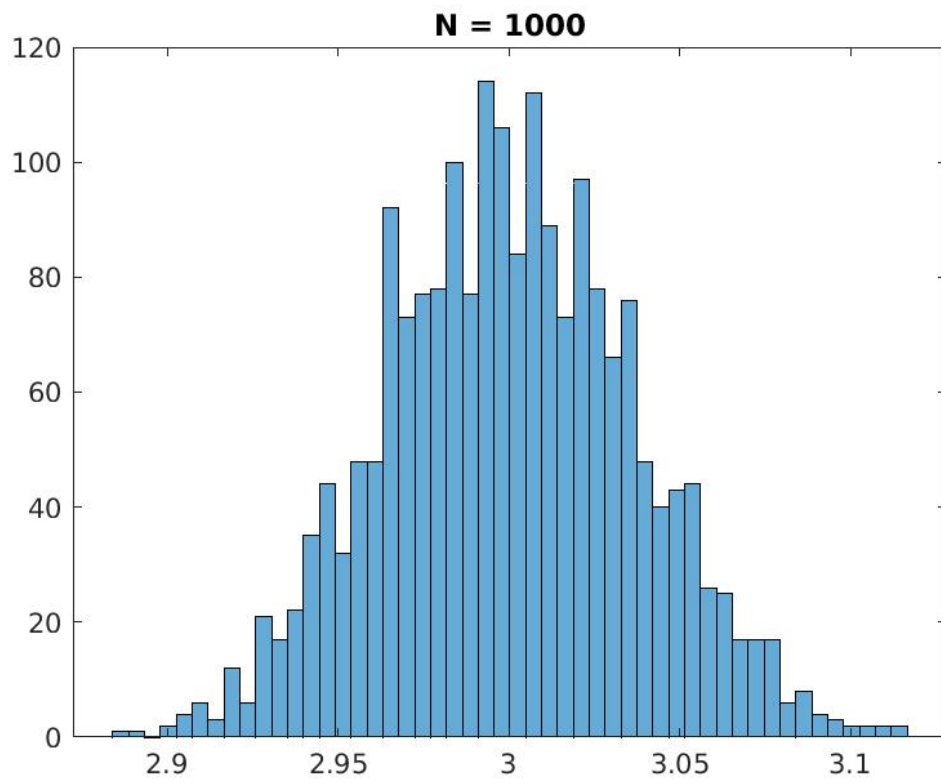
$$\Rightarrow t = \ln(1+s)$$

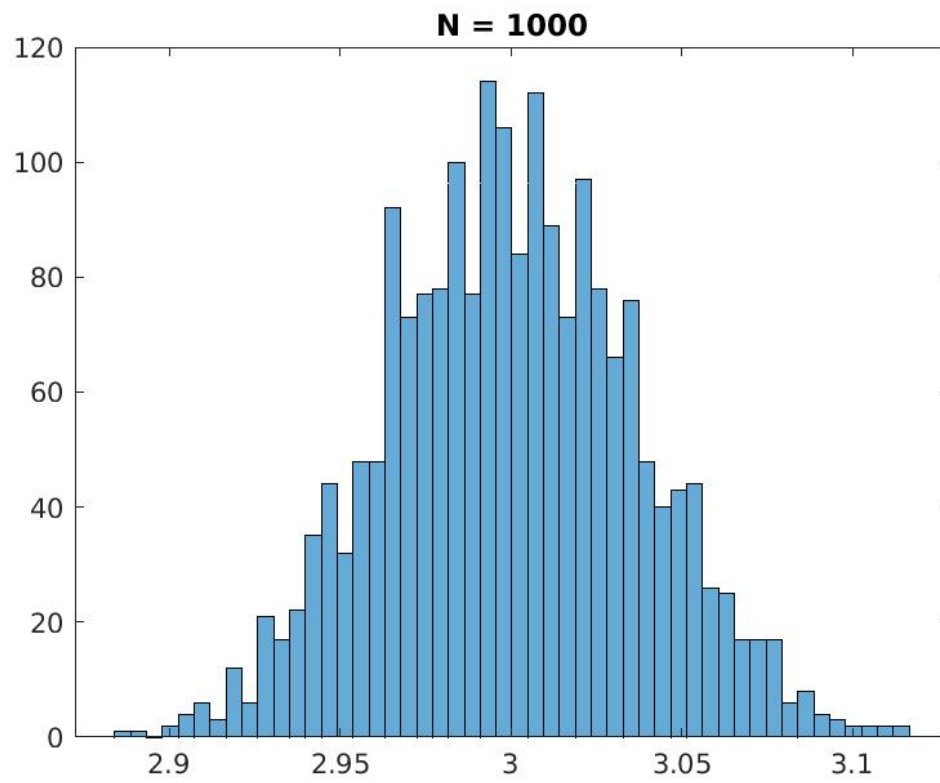
It is mini for minima as double derivative $= \mu e^t > 0$

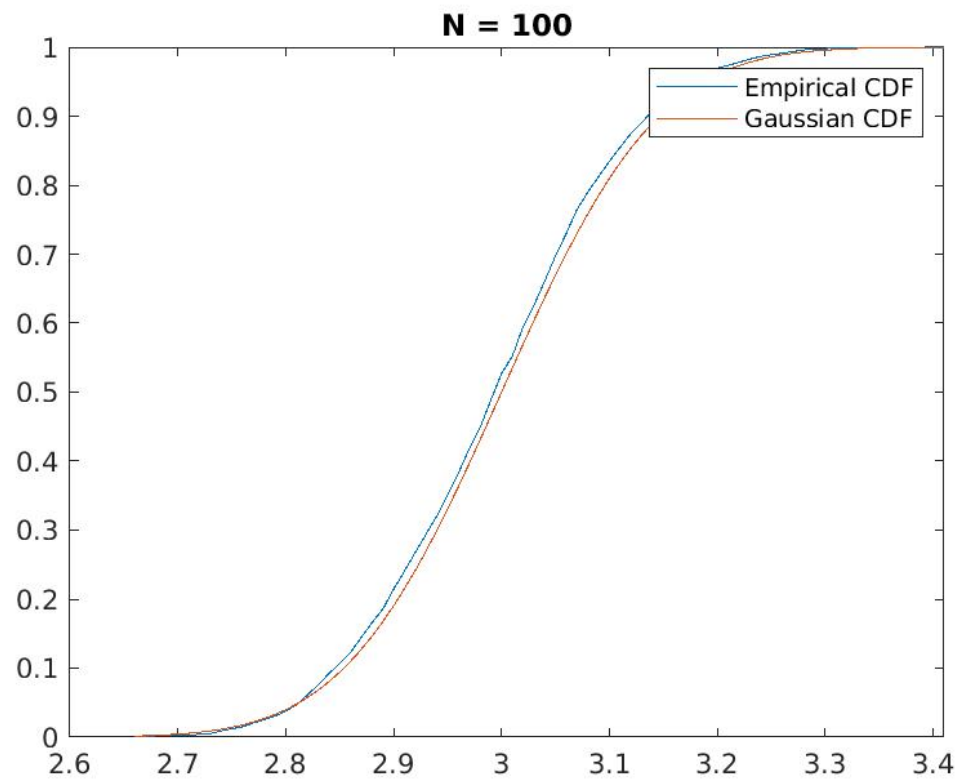
Question 5

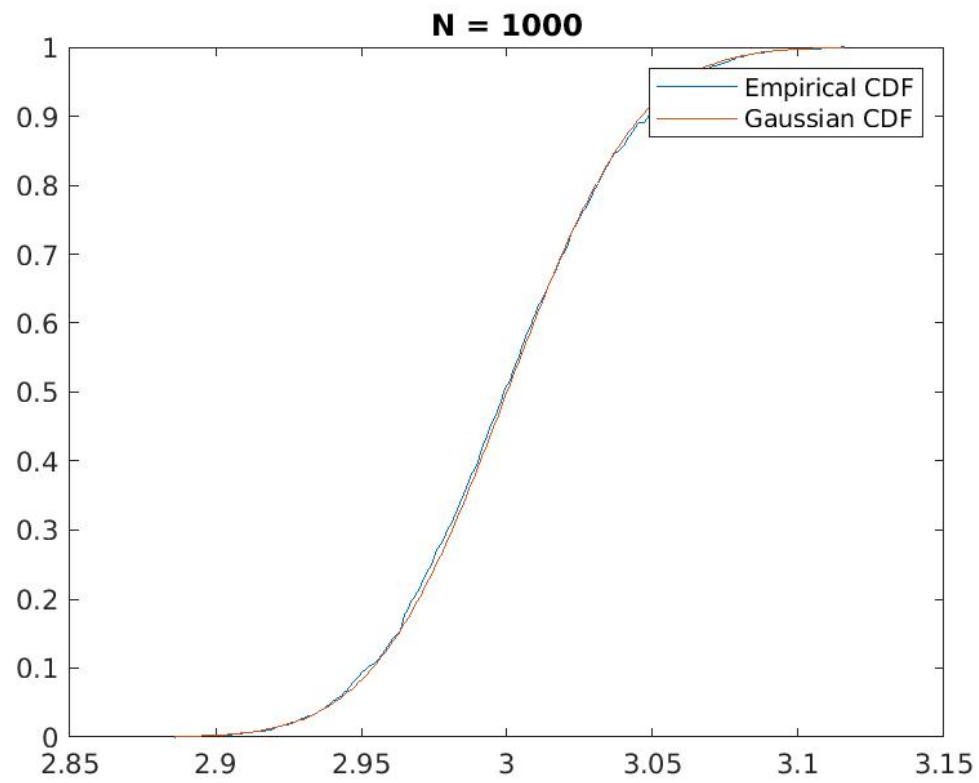
Code for this qsn is in file named 'q5.m'

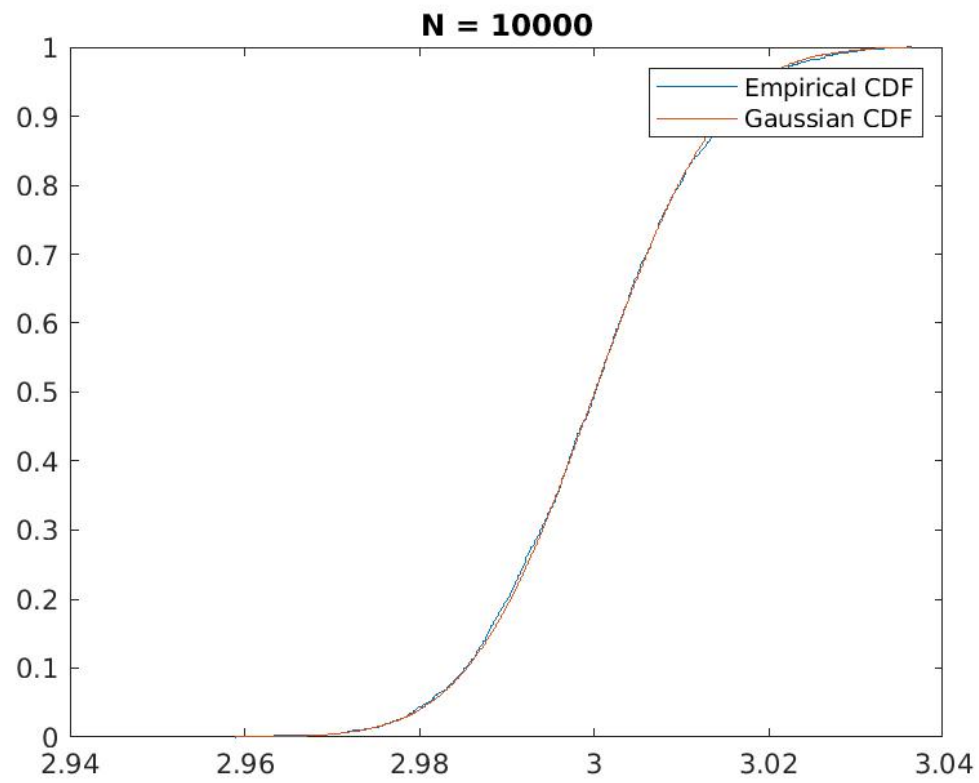


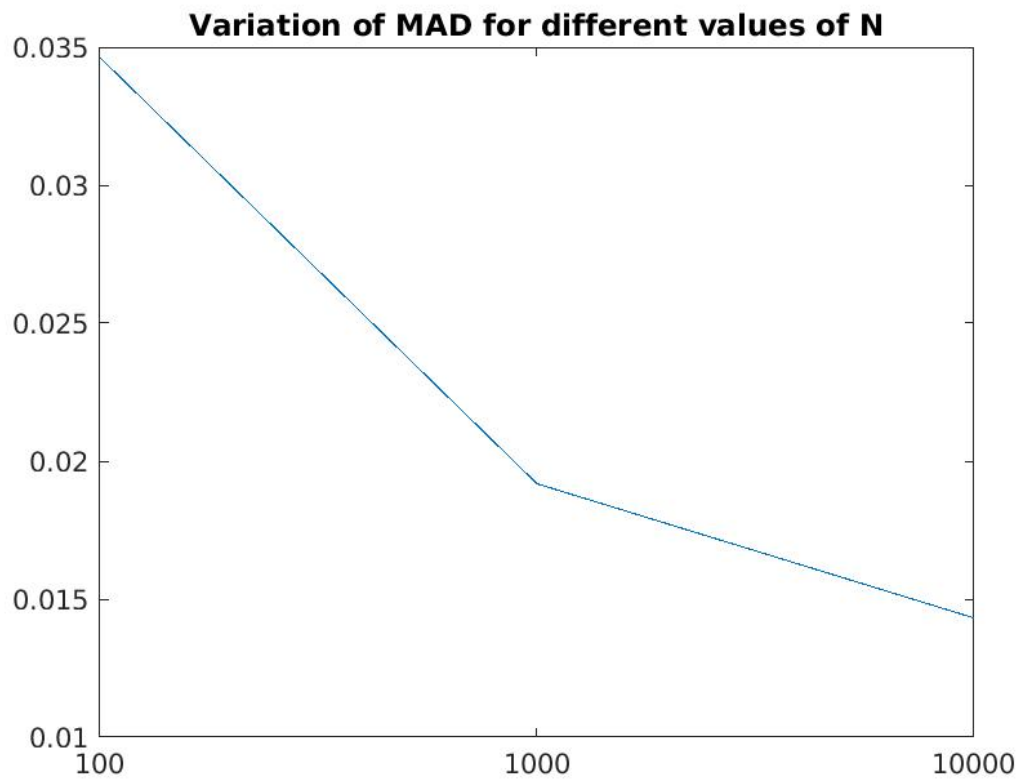












Question 6

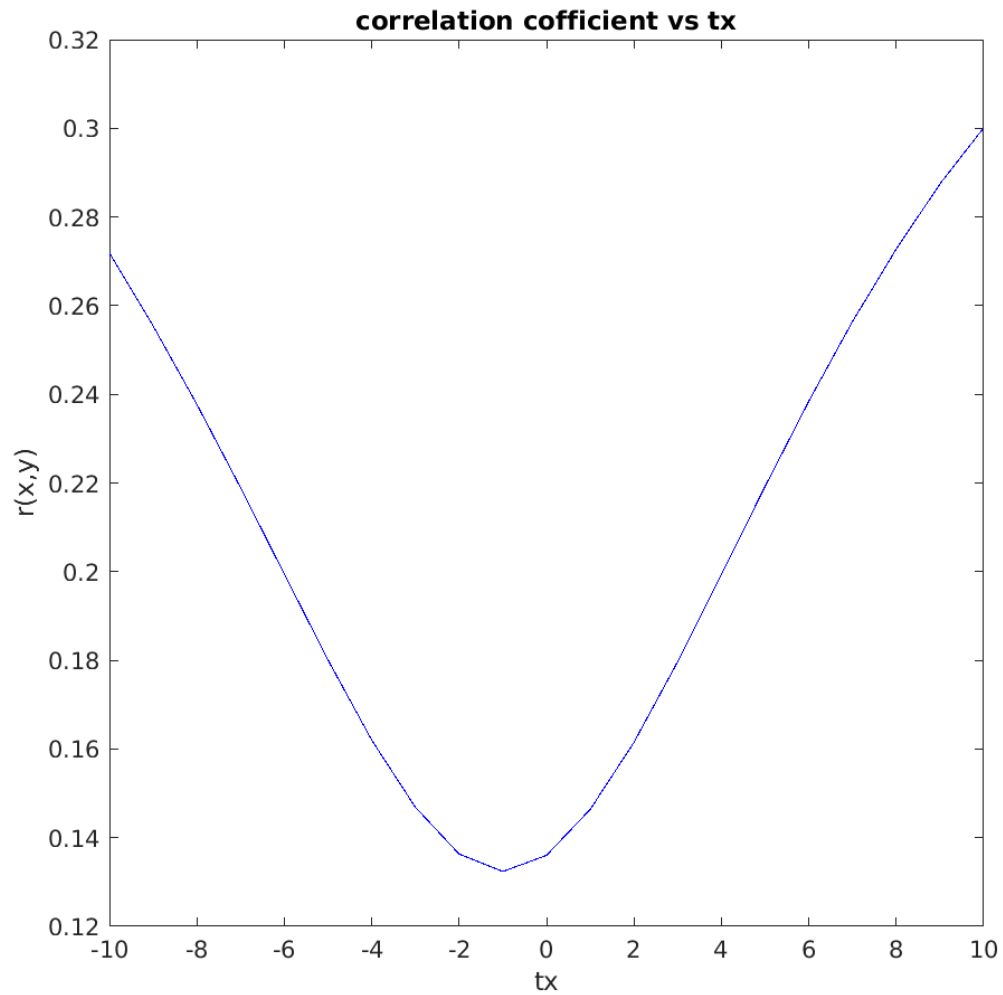


figure This plot correspond to T1.jpg

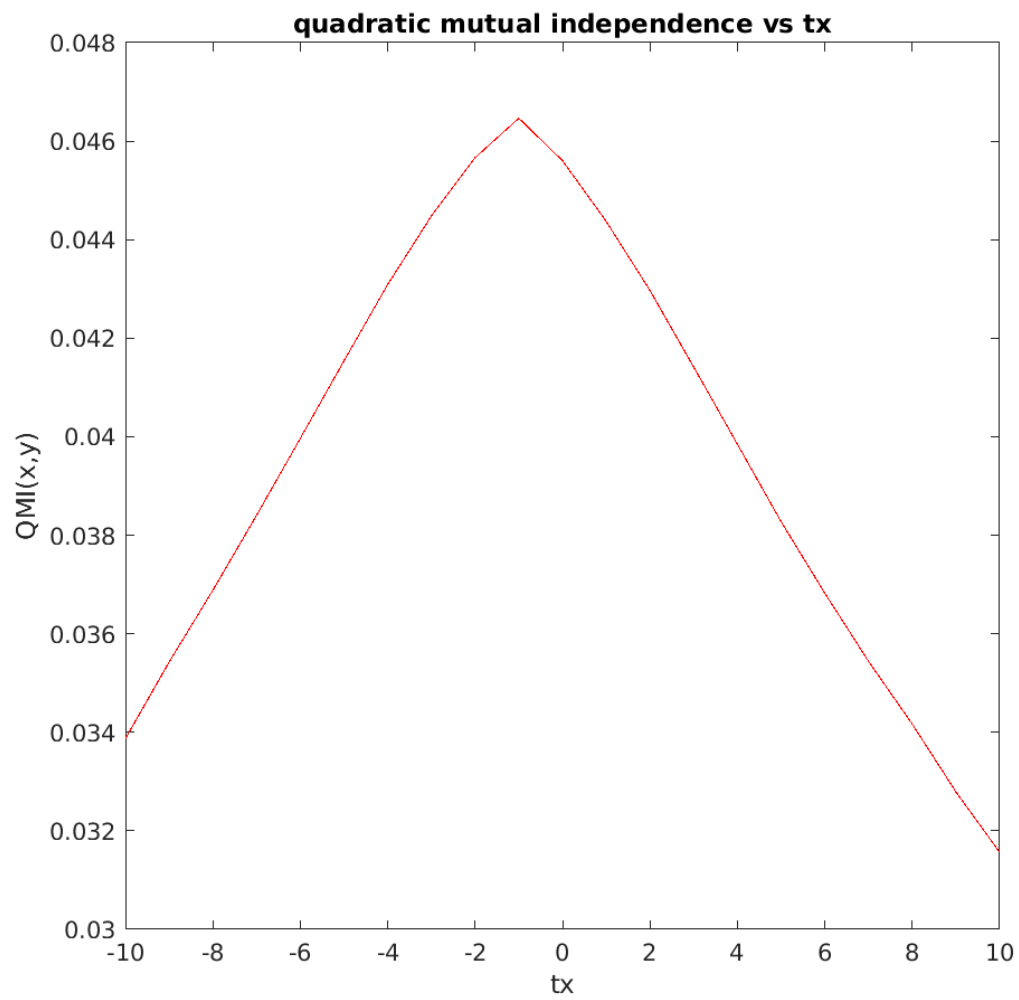


Figure 1: This plot correspond to T2.jpg

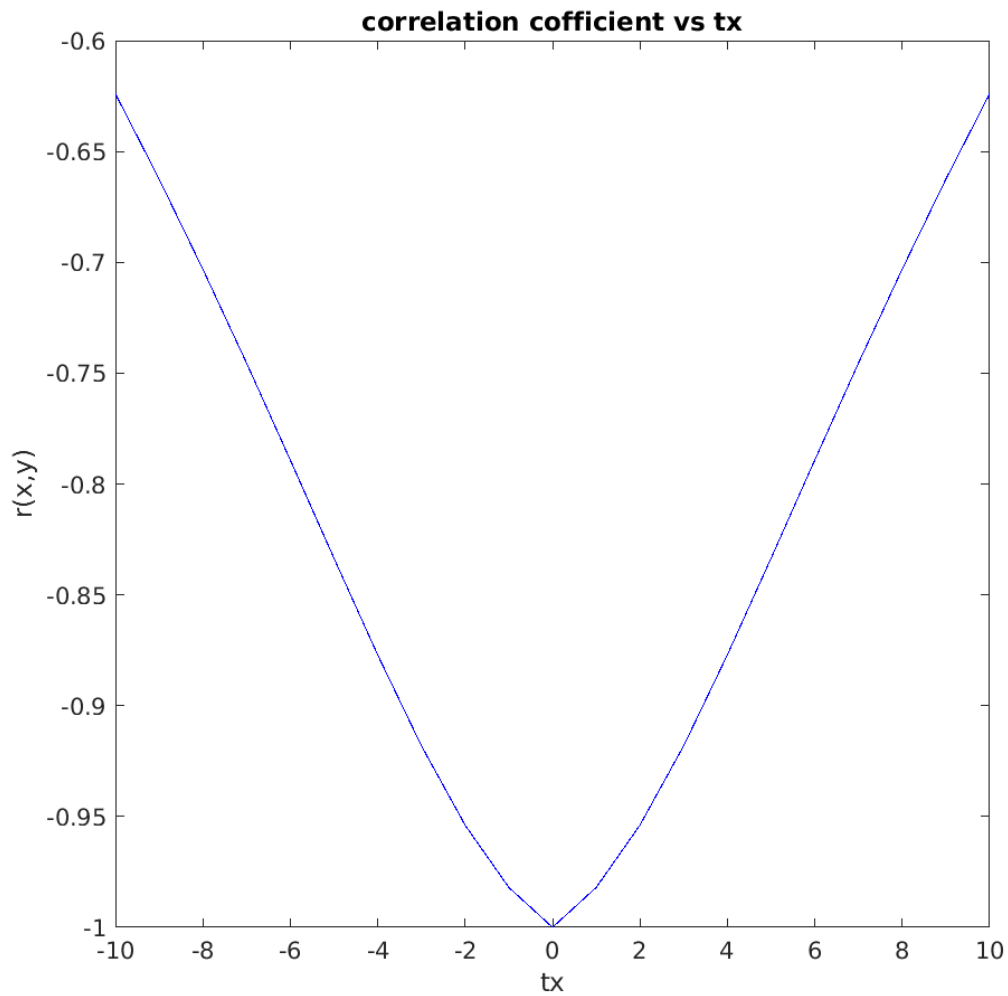


Figure 2: This plot correspond to T1.jpg and negative of T1.jpg

Question 7

7. Using the same definition as used in slide

$$x = \sum_{i=1}^K x_i$$

$$\therefore \phi_x(t) = \sum_{i=1}^K e^{j t_i x_i}$$

$$\phi_x(t_1, t_2, \dots, t_n) = \left(\sum_{i=1}^K e^{j t_i x_i} \right)^n$$

From slides

$$E[x_i x_j] = \frac{\partial}{\partial t_j} \frac{\partial}{\partial t_i} \phi_x(t) \Big|_{t=(0,0,\dots,0)}$$

where $t = (t_1, t_2, \dots, t_n)$

$$= \frac{\partial}{\partial t_j} e^{j n \pi i \left(\sum_{i=1}^K p_i e^{j t_i} \right)^{n-1}} \Big|_{t=(0,0,\dots)}$$

$$= e^{j n \pi i} \frac{\partial}{\partial t_j} \left(\sum_{i=1}^K p_i e^{j t_i} \right)^{n-1} \Big|_{t=(0,0,\dots)}$$

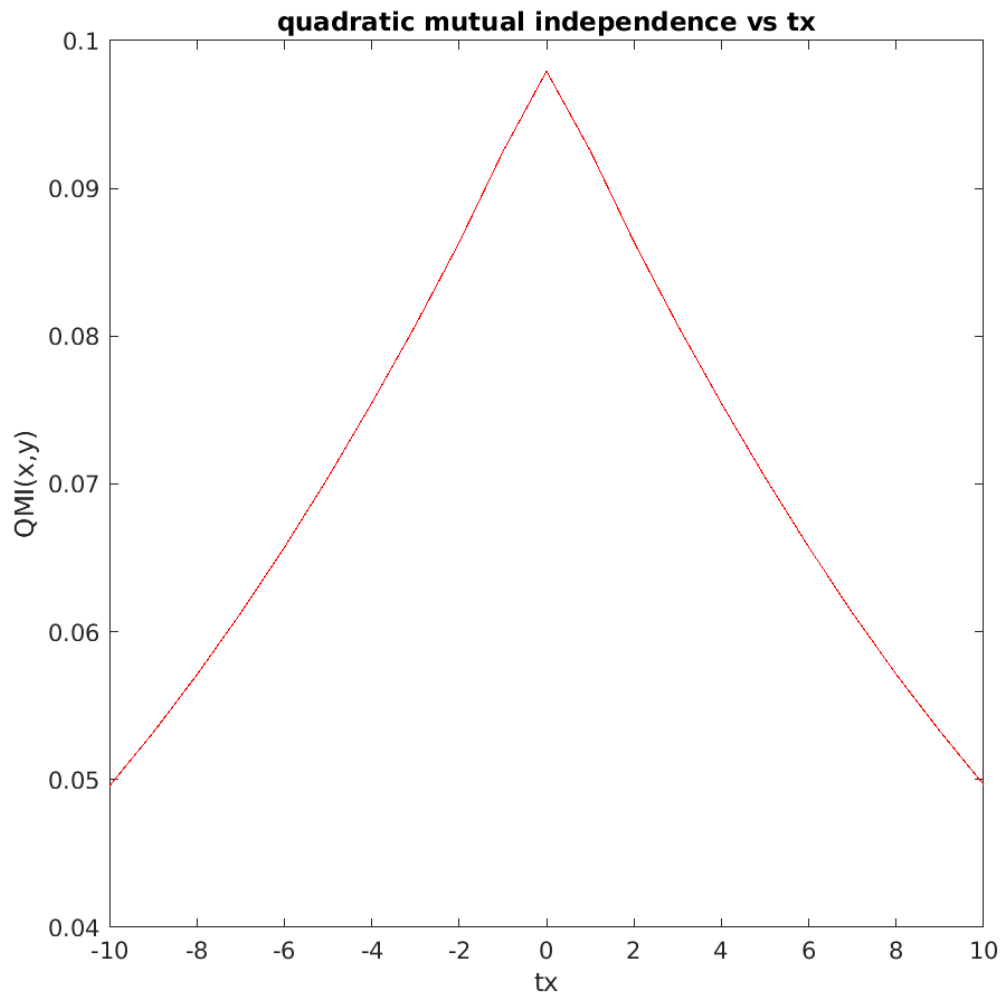


Figure 3: This plot correspond to T1.jpg and negative of T1.jpg

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$$E[x_i^2] = \frac{\partial^2}{\partial t_i^2} \phi_x(t) \Big|_{t=(0,0,\dots)}$$

where $t = (t_1, t_2, \dots, t_n)$

$$= \frac{\partial^2}{\partial t_i^2} \left(\sum p_i e^{t_i} \right)^n$$

$$= \frac{\partial}{\partial t_i} p_i n \left(\sum p_i e^{t_i} \right)^{n-1} \times e^{t_i}$$

$$= p_i n e^{t_i} \left(\sum p_i e^{t_i} \right)^{n-1} + p_i n e^{t_i} (n-1) \left(\sum p_i e^{t_i} \right)^{n-2} p_i e^{t_i}$$

At $\forall t_j = 0$
this becomes

$$p_i n + p_i n (n-1) p_i$$

$$= n p_i [1 + (n-1) p_i]$$

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