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1. For  $Y_1 = \max(X_1, \dots, X_N)$

$$cdf(x) = P(X_1 \leq x, X_2 \leq x, \dots, X_N \leq x)$$

As all  $X_i$  are independent random variables

$$= P(X_1 \leq x) \cdot P(X_2 \leq x) \cdot P(X_3 \leq x) \dots P(X_N \leq x)$$

$$= [F_X(x)]^N$$

$$pdf(x) = \frac{d}{dx} (cdf(x))$$

$$= N [F_X(x)]^{N-1} f_X(x)$$

For  $Y_2 = \min(X_1, \dots, X_N)$

$$cdf(x) = 1 - P(X_1 \geq x, X_2 \geq x, \dots, X_N \geq x)$$

As all  $X_i$  are independent random variables

$$= 1 - P(X_1 \geq x) \cdot P(X_2 \geq x) \dots P(X_N \geq x)$$

$$= 1 - \prod (1 - P(X_i \leq x))$$

$$= 1 - [1 - F_X(x)]^N$$

$$pdf(x) = \frac{d}{dx} cdf(x)$$

$$= -N[1 - F_X(x)]^{N-1} \cdot -f_X(x)$$

$$= N f_X(x) [1 - F_X(x)]^{N-1}$$

3.  $P(X - \mu \geq \tau)$   
 let's take  $Y = X - \mu$ .

$$= P(Y \geq \tau)$$

$$= P(Y + b \geq \tau + b) \leq P((Y + b)^2 \geq (\tau + b)^2)$$

as the domain of  $Y$  increases  
 for which the inequality holds

By Markov's inequality:

$$P((Y + b)^2 \geq (\tau + b)^2) \leq \frac{E((Y + b)^2)}{(\tau + b)^2}$$

Linearity  
 of expectation

$$= \frac{E(Y^2) + 2E(Y) + E(b^2)}{(\tau + b)^2}$$

$$= \frac{\sigma^2 + 0 + b^2}{(\tau + b)^2}$$

$$= \frac{\sigma^2 + b^2}{(1+b)^2}$$

We need to find such a value of  $b$  such that the term becomes minimum.

$$f(b) = \frac{\sigma^2 + b^2}{(1+b)^2}$$

$$f'(b) = \frac{(1+b)^2 (2b) - 2(\sigma^2 + b^2)(1+b)}{(1+b)^4} = 0$$

$$b(1+b) - 2(\sigma^2 + b^2) = 0$$

$$b + b^2 - 2\sigma^2 - 2b^2 = 0$$

$$b = \frac{\sigma^2}{1}$$

$$f(b) = \frac{\sigma^2 + \frac{\sigma^4}{1^2}}{(1 + \frac{\sigma^2}{1})^2}$$

$$= \frac{\sigma^2 + \sigma^4}{(1 + \sigma^2)^2}$$

$$= \frac{\sigma^2(1 + \sigma^2)}{(1 + \sigma^2)^2}$$

$$= \frac{\sigma^2}{1 + \sigma^2}$$

For  $\tau < 0$

Let  $\gamma = -\tau$

$$P(X - \mu < \tau) = P(-Y > \gamma) \leq \frac{\sigma^2}{\gamma^2 + \sigma^2}$$

Taking the complement of above set, we get

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



Q2  $X \sim \sum_{i=1}^K p_i N(\mu_i, \sigma_i^2)$

Since  $X = X_i$  with probability  $p_i$

$$\begin{aligned}\phi_X(t) &= \sum_{i=1}^K p_i \phi_{X_i}(t) \\ &= \sum_{i=1}^K p_i e^{(\mu_i t + \sigma_i^2 t^2 / 2)}\end{aligned}$$

$$\phi_X'(0) = E(X) = \left. \frac{\partial}{\partial t} \left[ \sum_{i=1}^K p_i e^{(\mu_i t + \sigma_i^2 t^2 / 2)} \right] \right|_{t=0}$$

$$\boxed{E(X) = \sum_{i=1}^K p_i \mu_i}$$

$$\phi_X''(0) = E(X^2) = \left. \frac{\partial^2}{\partial t^2} \left[ \sum_{i=1}^K p_i e^{(\mu_i t + \sigma_i^2 t^2 / 2)} \right] \right|_{t=0}$$

$$= \sum_{i=1}^K \frac{\partial}{\partial t} \left[ p_i (\mu_i + \sigma_i^2 t) e^{(\mu_i t + \sigma_i^2 t^2 / 2)} \right]$$

$$= \sum_{i=1}^K \left[ p_i (\mu_i + \sigma_i^2 t)^2 e^{(\mu_i t + \sigma_i^2 t^2 / 2)} + p_i \sigma_i^2 e^{(\mu_i t + \sigma_i^2 t^2 / 2)} \right]_{t=0}$$

$$= \sum_{i=1}^K p_i (\mu_i^2 + \sigma_i^2)$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2$$

$$= \sum_{i=1}^K p_i (\mu_i^2 + \sigma_i^2) - \left( \sum_{i=1}^K p_i \mu_i \right)^2$$

$$\phi_Z(t) = E(e^{tx})$$

$$= E(e^{t \sum_{i=1}^N p_i X_i})$$

as all  $X_i$  are independent

$$= \prod_{i=1}^N E(e^{t p_i X_i})$$

$$= \prod_{i=1}^N (e^{p_i \mu_i t + \frac{1}{2} p_i^2 \sigma_i^2 t^2})$$

$$\phi_Z(t) = e^{\left(\sum_{i=1}^N \mu_i p_i\right)t + \frac{1}{2} \left(\sum_{i=1}^N p_i^2 \sigma_i^2\right)t^2}$$

As pdf is unique for a given moment generating function.

$$PDF(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

Where:  $\mu = \sum_{i=1}^N \mu_i p_i$

$$\sigma^2 = \sum_{i=1}^N p_i^2 \sigma_i^2$$

as  $MGF(Y) \sim N(\mu, \sigma^2)$

whose PDF is the one given above.

Since  $\phi_Z(t) = e^{\sum \mu_i p_i t + \frac{1}{2} \sum \sigma_i^2 p_i^2 t^2}$

$$\phi_Z'(t) \big|_{t=0} = E(Z) = \sum \mu_i p_i$$

$$\phi_Z''(t) = \frac{d}{dt} \left( e^{\sum \mu_i p_i t + \frac{1}{2} \sum \sigma_i^2 p_i^2 t^2} \right) = \left( \sum \mu_i p_i \right) e^{\sum \mu_i p_i t + \frac{1}{2} \sum \sigma_i^2 p_i^2 t^2} + \left( \sum \sigma_i^2 p_i^2 \right) e^{\sum \mu_i p_i t + \frac{1}{2} \sum \sigma_i^2 p_i^2 t^2}$$

$$\phi_Z''(t) \big|_{t=0} = E(Z^2) = \left( \sum \mu_i p_i \right)^2 + \left( \sum \sigma_i^2 p_i^2 \right)$$

$$\text{Var}(Z) = E(Z^2) - [E(Z)]^2$$

$$= \sum \sigma_i^2 p_i^2$$



Q.4 For  $t > 0$   
 using Markov's inequality  $X \geq x \Rightarrow tX \geq tx \ [t > 0]$

$$P(X \geq x) = P(e^{tx} \geq e^{tx}) \leq \frac{E(e^{tx})}{e^{tx}} = \phi_x(t) e^{-tx}$$

for  $t < 0$

$$X \leq x \Rightarrow tX \geq tx$$

$$P(X \leq x) = P(e^{tx} \geq e^{tx}) \leq \frac{E(e^{tx})}{e^{tx}} = \phi_x(t) e^{-tx}$$

$$P(X > (1+\delta)\mu) \leq e^{-t(1+\delta)\mu} \phi_x(t) \quad [\text{By above inequality}]$$

$$= \frac{\phi_x(t)}{e^{(1+\delta)t\mu}} = \frac{E(e^{t\sum x_i})}{e^{(1+\delta)t\mu}}$$

$$= \frac{\prod_i E(e^{tx_i})}{e^{(1+\delta)t\mu}} \quad [\text{Since } x_i \text{ are i.i.d.}]$$

$$= \frac{\prod (p_i e^{t\mu} + 1 - p_i)}{e^{(1+\delta)t\mu}}$$

using  $1+x \leq e^x$

$$\leq \frac{\prod e^{(e^t-1)p_i}}{e^{(1+\delta)t\mu}}$$

$$= \frac{e^{\sum p_i(e^t-1)}}{e^{(1+\delta)t\mu}} = \frac{e^{\mu(e^t-1)}}{e^{(1+\delta)t\mu}}$$

Since

$$P(X > (1+\delta)\mu) \leq \frac{e^{\mu(e^t-1)}}{e^{(1+\delta)t\mu}} \text{ holds } \forall t \geq 0$$

It will also hold for  $t = t_0$  which minimises R.H.S.

$$\frac{\partial}{\partial t} \frac{e^{\mu(e^t-1)}}{e^{(1+\delta)t\mu}} = 0 \Rightarrow \frac{\partial}{\partial t} [\mu(e^t-1) - (1+\delta)t\mu] = 0$$

$$[t = \log(1+\delta)] \text{ minimises } \Rightarrow \mu e^t - \mu(1+\delta) = 0$$

At  $t = \log(1+\delta)$

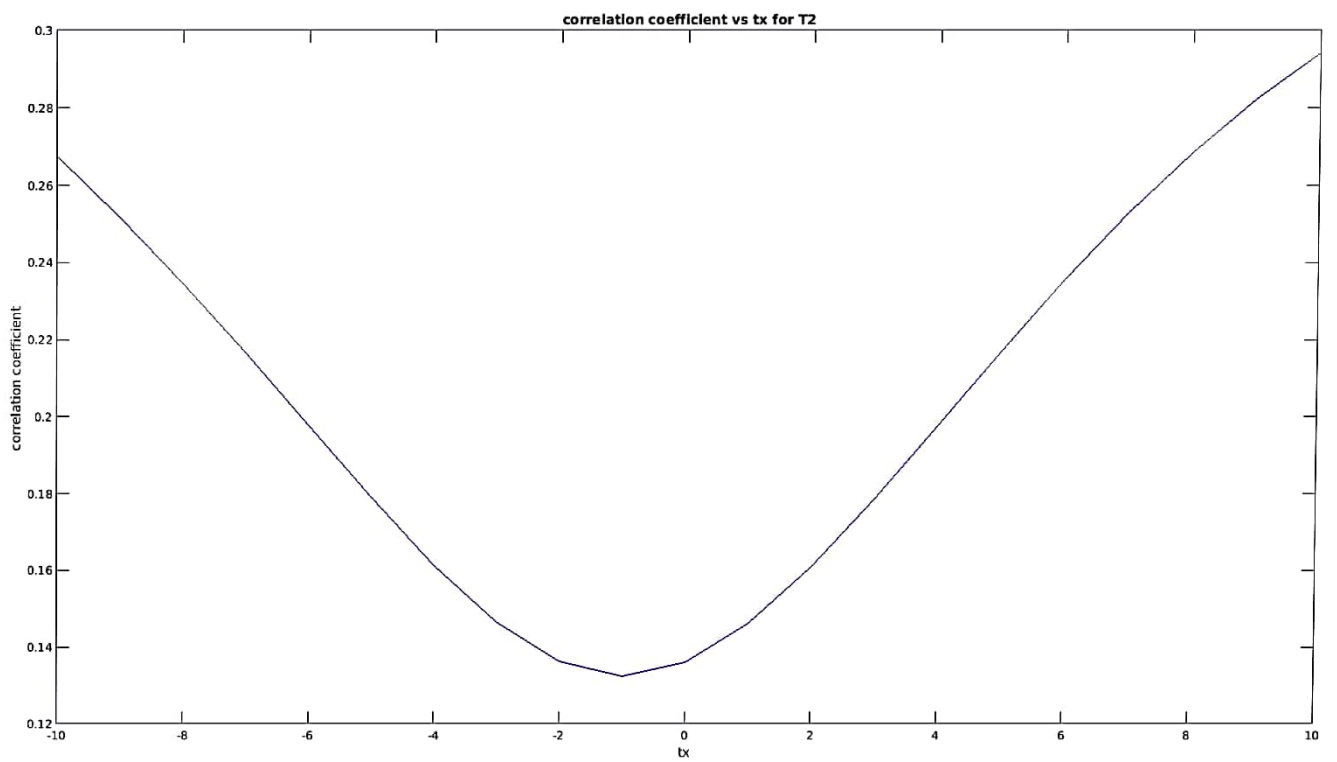
$$P(X > (1+\delta)\mu) \leq \frac{e^{s\mu}}{e^{(1+\delta)\mu \log(1+\delta)}}$$

$$\left[ \frac{\partial^2}{\partial t^2} \frac{e^{\mu(e^t-1)}}{e^{(1+\delta)t+\mu}} = (+ve) \frac{\partial}{\partial t} \times [\mu e^t - \mu(1+\delta)] = (+ve) \mu e^t > 0 \right.$$

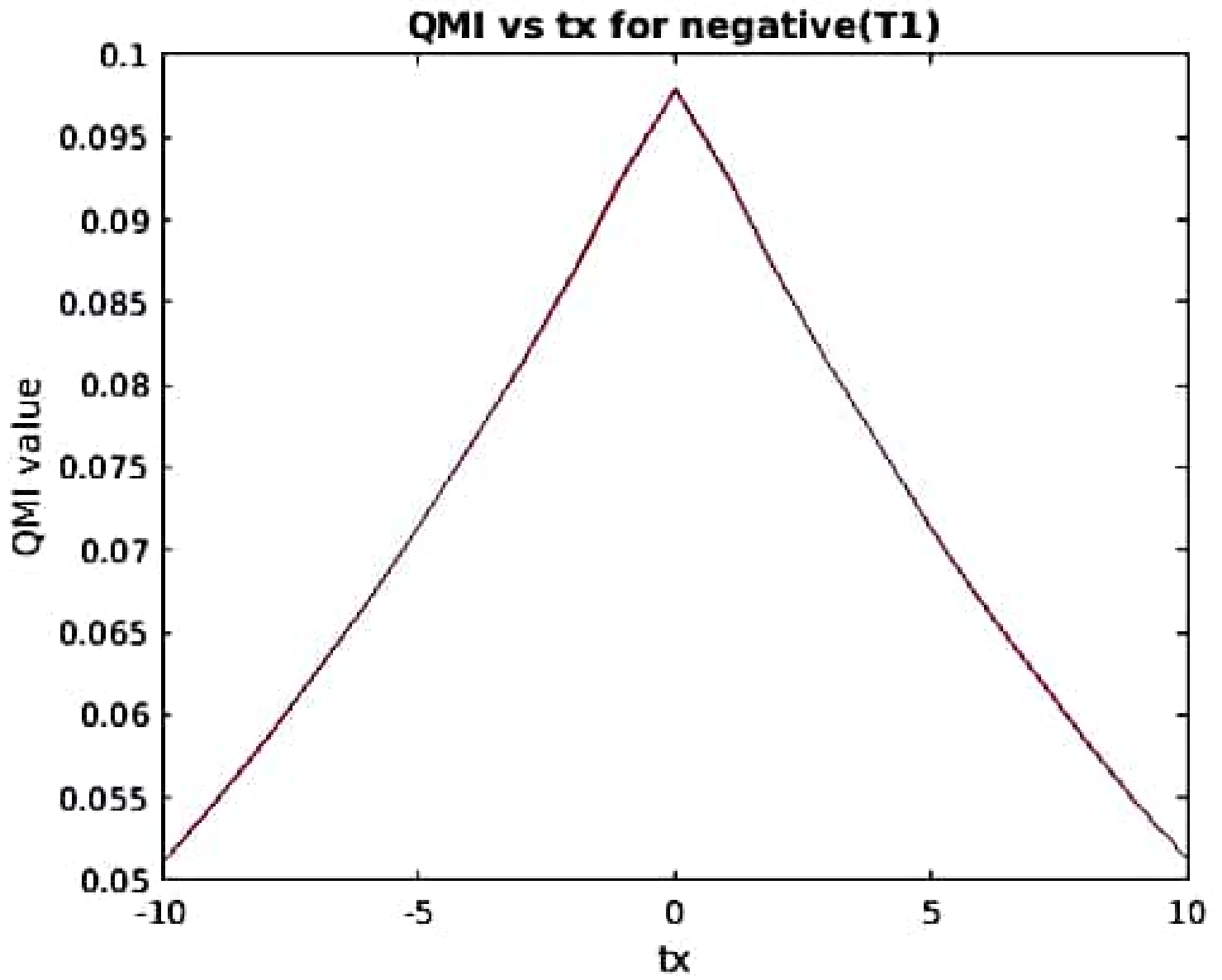
hence  $t = \log(1+\delta)$   
is minima].

8.6 When the two images  $I_1$  &  $I_2$  are aligned fully ( $I_2$  is  $I_1$  with shift along x-axis as 0) i.e.  $S=0$ , then both the images are highly dependent on each other which is reflected in QMI plot but since correlation coefficient uses only mean & variance of intensities (much of the information of PMF not used), we don't see the same behaviour in correlation plot as in QMI plot.  $\odot$

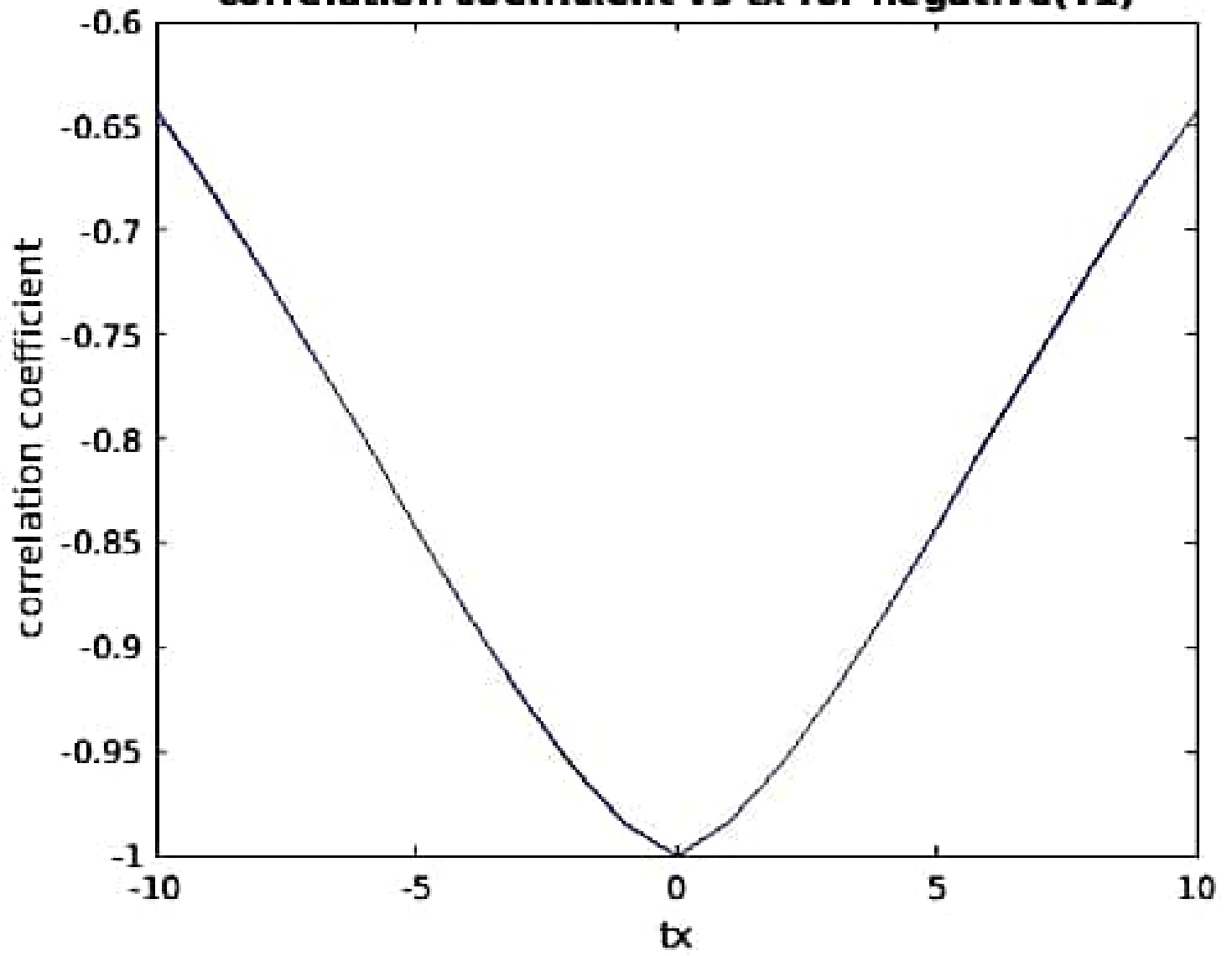
But when  $I_2$  is negative of  $I_1$ , then both QMI & correlation coefficient show the same behaviour in terms of dependence between  $I_1$  &  $I_2$  values.







**correlation coefficient vs tx for negative(T1)**



**QMI vs tx for T2**

