

CSE 544.01 Probability and Statistics for Data Scientists

Assignment - 3 Team Members

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①

Show that

$$MSE = \text{bias}^2(\hat{\theta}) + \text{var}(\hat{\theta})$$

$\hat{\theta}$ is estimator of $\theta \leftarrow$ true parameter of unknown distribution X

w.k.t

$$MSE = \text{Mean Squared Error} = MSE(\hat{\theta}) = E(\theta - \hat{\theta})^2$$

$$MSE(\hat{\theta}) = E[(\theta - \hat{\theta})^2]$$

~~LHS~~ Let $E(\hat{\theta})$ be a expectation of Random Variable

$\therefore E(\hat{\theta})$ is a constant

$$E[\hat{\theta} - E(\hat{\theta})] \stackrel{\text{def}}{=} E(\hat{\theta}) - E(\hat{\theta}) = 0$$

Consider LHS

$$\begin{aligned} E((\theta - \hat{\theta})^2) &= E((\theta - E(\hat{\theta}) + E(\hat{\theta}) - \hat{\theta})^2) \quad \left[\begin{array}{l} \text{Adding &} \\ \text{subtracting} \\ E(\hat{\theta}) \end{array} \right] \\ &= E((\theta - E(\hat{\theta}))^2 + (E(\hat{\theta}) - \hat{\theta})^2 + 2(\theta - E(\hat{\theta}))(E(\hat{\theta}) - \hat{\theta})) \\ &\stackrel{\text{LOE}}{=} E((\theta - E(\hat{\theta}))^2) + E((E(\hat{\theta}) - \hat{\theta})^2) \\ &\quad + 2(\theta - E(\hat{\theta})) E(E(\hat{\theta}) - \hat{\theta}) \quad - ① \end{aligned}$$

$\because \theta$ is constant, $\theta - E(\hat{\theta})$ is constant, θ is true parametric constant.

W.K.T

$$\text{bias}(\hat{\theta}) = E[\hat{\theta}] - \theta \quad \& \quad \text{var}(\hat{\theta}) = E[(\hat{\theta} - E[\hat{\theta}])^2]$$

From ①

$$= [E[\hat{\theta}] - \theta]^2 + E[(\hat{\theta} - E[\hat{\theta}])^2] + 2(\theta - E[\hat{\theta}])(0)$$

$$= \text{bias}^2(\hat{\theta}) + \text{var}(\hat{\theta})$$

$$= \text{R.H.S}$$

$$\therefore \text{MSE} = \text{bias}^2(\hat{\theta}) + \text{var}(\hat{\theta})$$

Hence proved

Another way of solving

Consider L.H.S

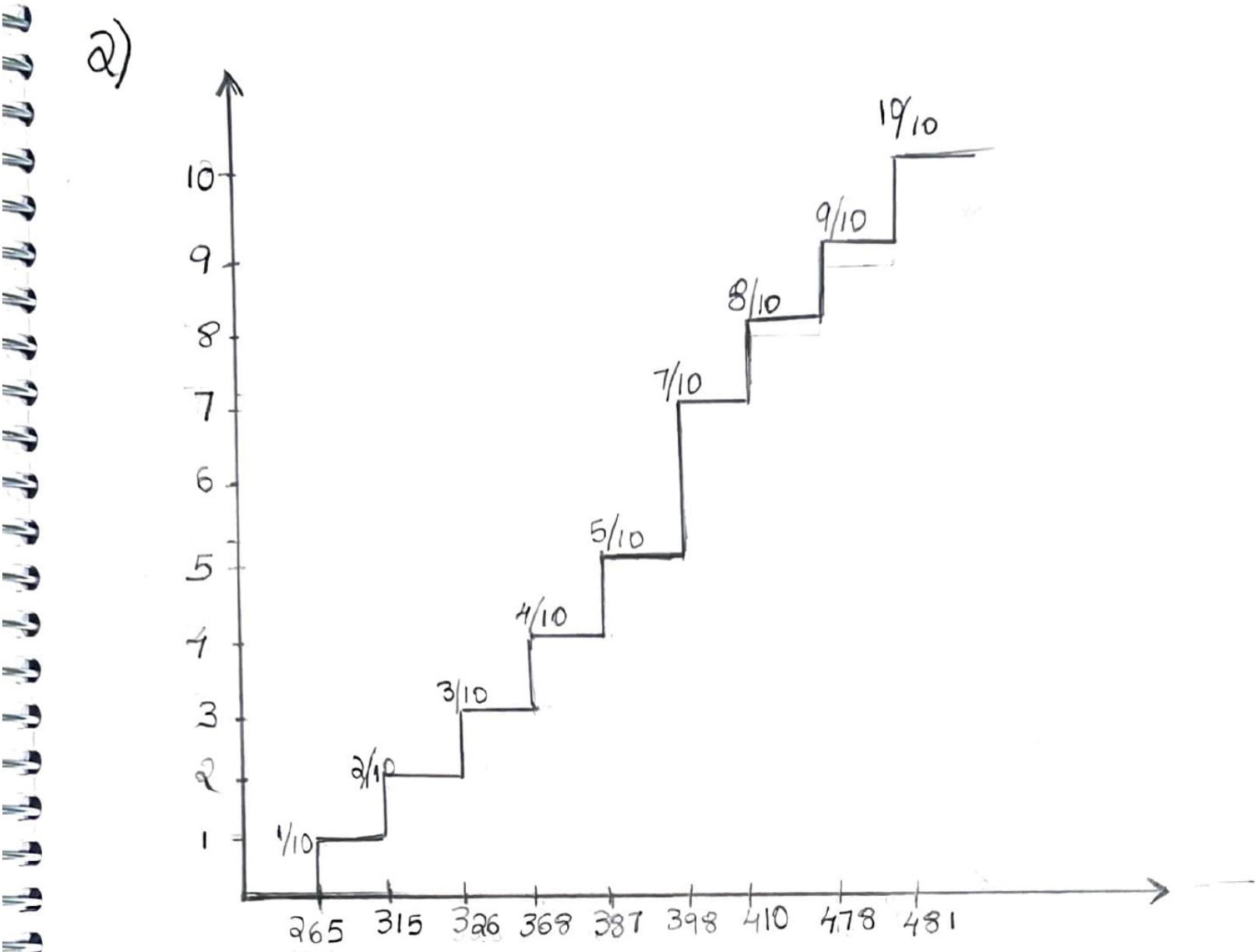
$$\text{MSE} = E[(\hat{\theta} - \theta)^2] = E[\hat{\theta}^2 + \theta^2 - 2\hat{\theta}\theta]$$
$$= E[\hat{\theta}^2] - 2\theta E[\hat{\theta}] + \theta^2 \quad \text{--- ①}$$

$$\begin{aligned} \text{R.H.S} \\ \text{bias}^2(\hat{\theta}) + \text{var}(\hat{\theta}) &= (E[\hat{\theta}] - \theta)^2 + E[(\hat{\theta} - E[\hat{\theta}])^2] \\ &= E[\hat{\theta}]^2 + \theta^2 - 2E[\hat{\theta}]\theta + E[\hat{\theta}^2] - (E[\hat{\theta}])^2 \\ &= E[\hat{\theta}^2] - 2E[\hat{\theta}]\theta + \theta^2 - \theta^2 \end{aligned}$$

From ① & ②

$$\therefore \text{L.H.S} = \text{R.H.S}$$
$$\therefore \text{MSE} = \text{bias}^2(\hat{\theta}) + \text{var}(\hat{\theta})$$

2)



$$D = \{265, 315, 326, 368, 387, 398, 410, 478, 481\}$$

Q) 3 a) Given $D = \{x_1, x_2, \dots, x_n\}$ be a set of i.i.d.
 \hat{F} is the eCDF

$$\hat{F}(\alpha) = \sum_{i=1}^n \frac{I(x_i \leq \alpha)}{n}$$

eCDF

$$E(\hat{F}(\alpha)) = E\left(\sum_{i=1}^n \frac{I(x_i \leq \alpha)}{n}\right)$$

$$\stackrel{\text{LOE}}{=} \frac{1}{n} \sum_{i=1}^n E(I(x_i \leq \alpha)) \stackrel{\text{i.i.d.}}{=} \frac{1}{n} \underset{(n)}{\sum} E(I(x_i \leq \alpha))$$

$$= E(I(x \leq \alpha))$$

We know $E(I(x)) = P_\gamma(x)$

$$= P_\gamma(x \leq \alpha)$$

$$= F(\alpha)$$

$$\therefore E[\hat{F}(\alpha)] = F(\alpha)$$

$$^3 \text{ (b)} \quad \text{Bias}(\hat{F}) = 0$$

$$\left[\text{bias}(\hat{\theta}) = E[\hat{\theta}] - \theta \right]$$

From (a) we know that $E[\hat{F}(\alpha)] = F$

$$\therefore \text{bias}(\hat{F}) = \hat{F} - F = 0$$

$$\left[\text{bias}(\hat{F}) = 0 \right]$$

$$(c) \quad \text{se}(\hat{F}) = \sqrt{\text{Var}(\hat{F})}$$

$$\begin{aligned} \text{Var}(\hat{F}(\alpha)) &= \text{Var}\left(\sum_{i=1}^n \frac{I(X_i \leq \alpha)}{n}\right) \\ &= \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n I(X_i \leq \alpha)\right) \stackrel{\text{i.i.d}}{\underset{\text{i.i.d}}{\equiv}} \frac{1}{n^2} \sum_{i=1}^n \text{Var}(I(X_i \leq \alpha)) \\ &\stackrel{\text{iid}}{=} \frac{1}{n^2} \cdot n \text{Var}(I(X \leq \alpha)) \end{aligned}$$

$$= \frac{1}{n} \text{Var}(I(X \leq \alpha))$$

bernoulli

The distribution is in the form of
distribution.

[W.K.T Variance of ~~binomial distribution~~ indicator RV is $P(1-P)$]

$$= \frac{1}{n} \text{Var}(I(x \leq \alpha))$$

$$= \frac{1}{n} P_\theta(x \leq \alpha) (1 - P_\theta(x \leq \alpha))$$

$$= \frac{1}{n} F(\alpha)(1 - F(\alpha))$$

$$\text{Var}(\hat{F}(\alpha)) = \frac{1}{n} F(\alpha)(1 - F(\alpha))$$

$$\Rightarrow \text{Se}(\hat{F}) = \sqrt{\frac{F(1-F)}{n}}$$

\approx

(d) If $\text{bias}(\hat{\theta}) \xrightarrow{n \rightarrow \infty} 0$ and $\text{se}(\hat{\theta}) \xrightarrow{n \rightarrow \infty} 0$ then $\hat{\theta}$ is a ^{consistent} estimator of θ

$$\text{From (b)} \quad \text{bias}(\hat{F}) = 0 \quad (\text{irrespective of } n)$$

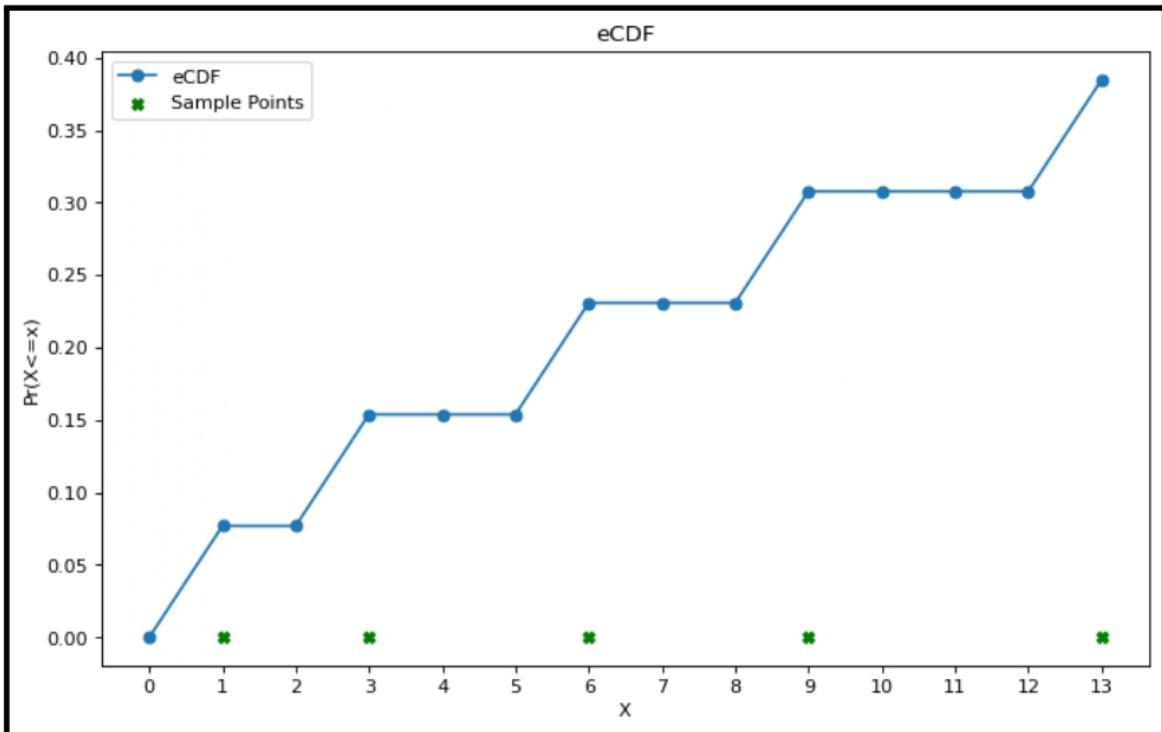
$$\text{From (c)} \quad \text{se}(\hat{F}) = \sqrt{\frac{1}{n} F(1-F)} \quad \text{as } n \rightarrow \infty \quad \frac{1}{n} = 0$$

$$\therefore \text{se}(\hat{F}(\alpha)) \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

$\therefore \hat{F}$ is a consistent estimator of F .

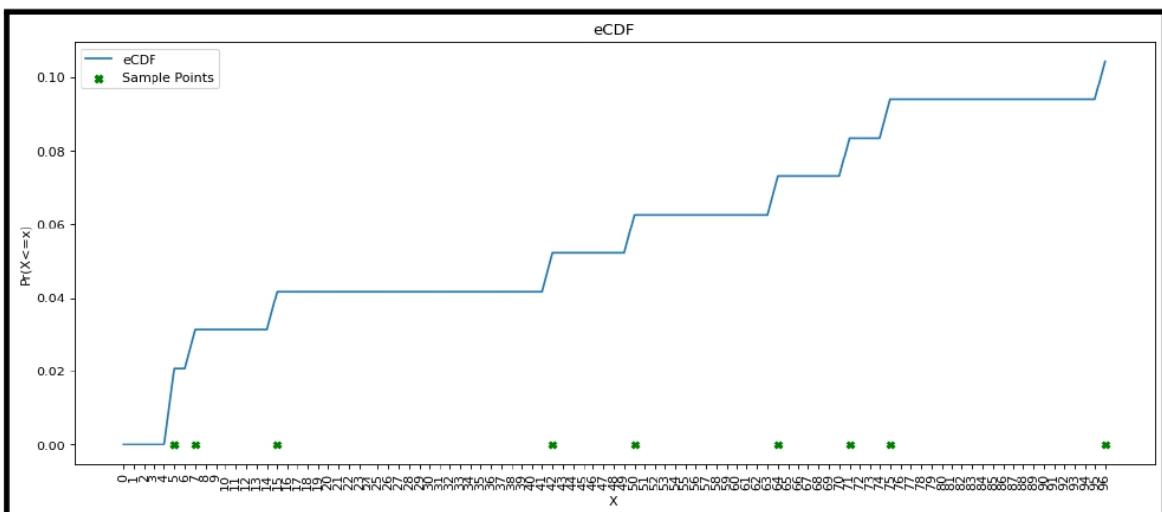
4

A)

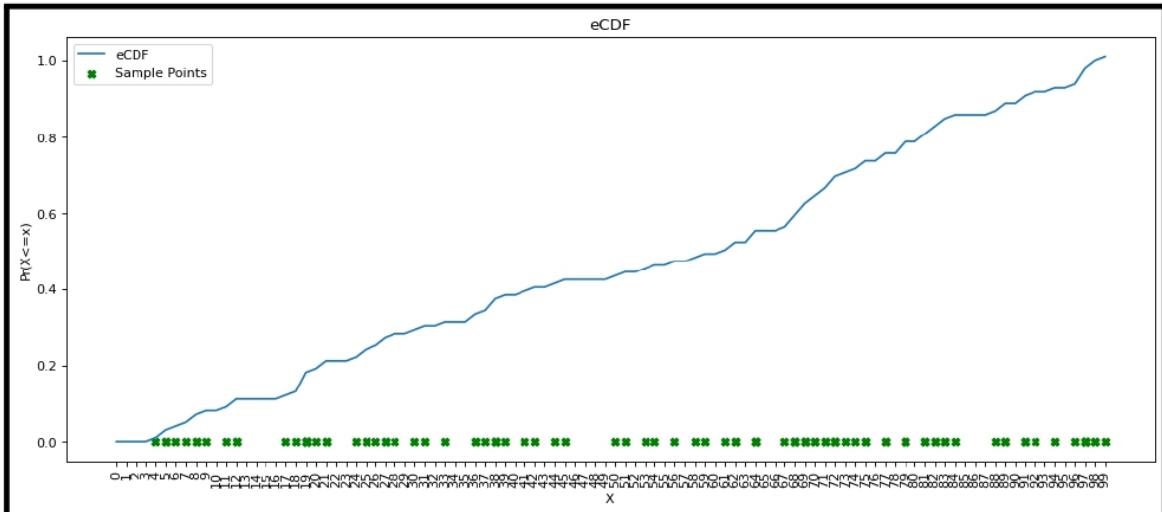


B)

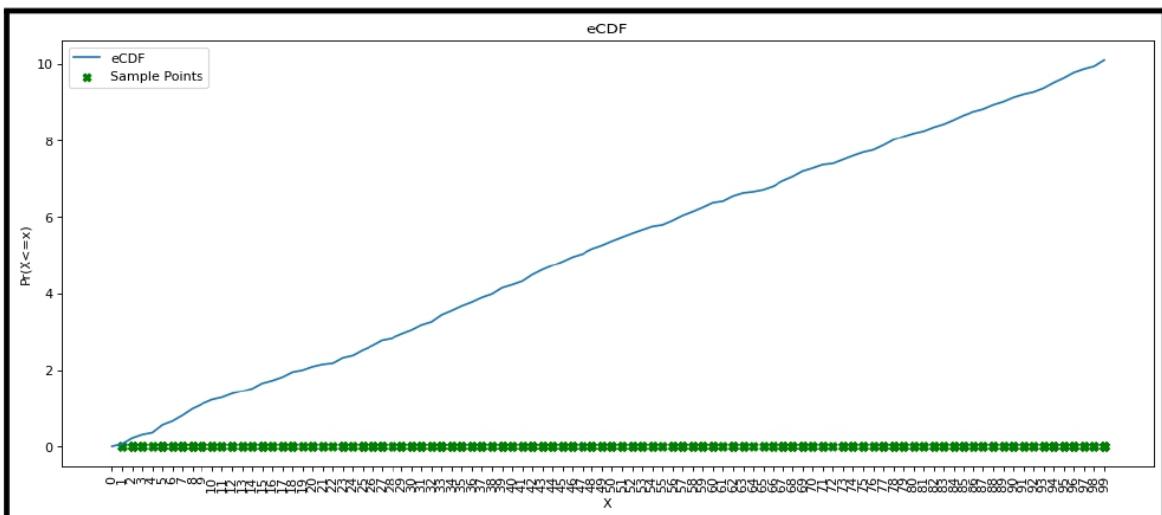
N=10



N=100

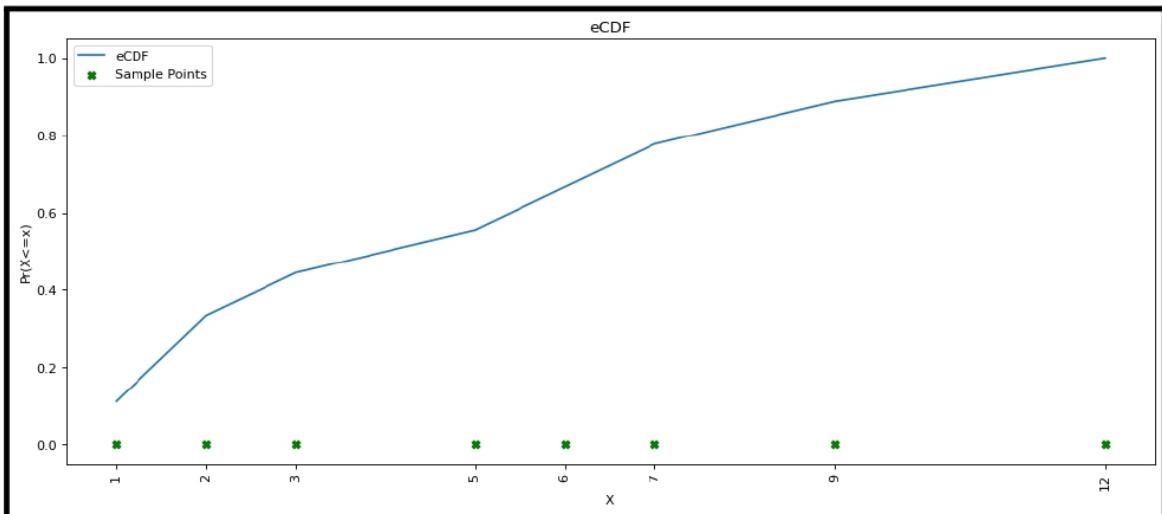


N=1000



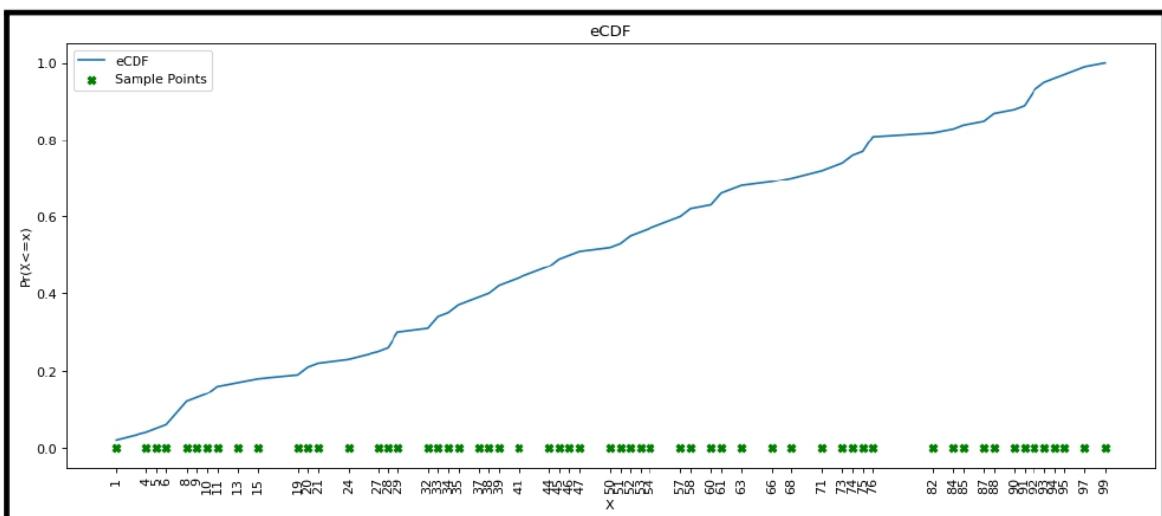
As the N value increases, the CDF becomes a straight line (The steps decrease in the CDF).

C)

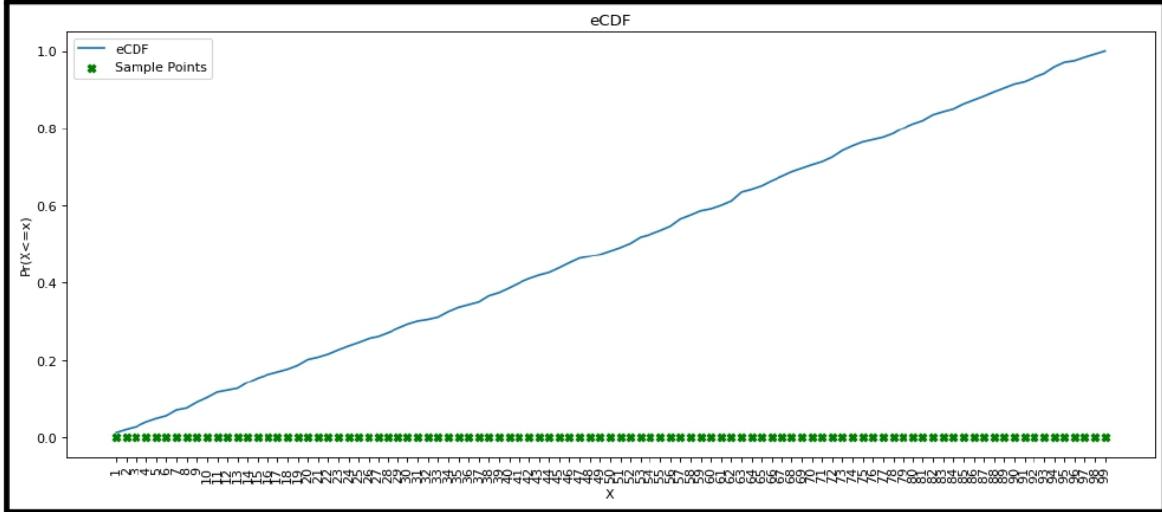


D)

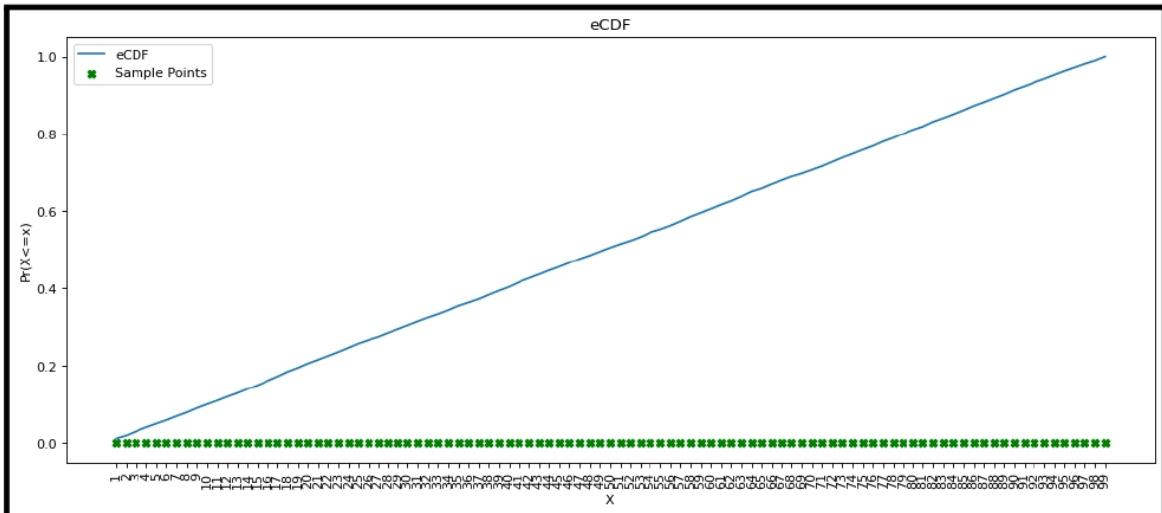
N=10, M=10



N=10, M=100

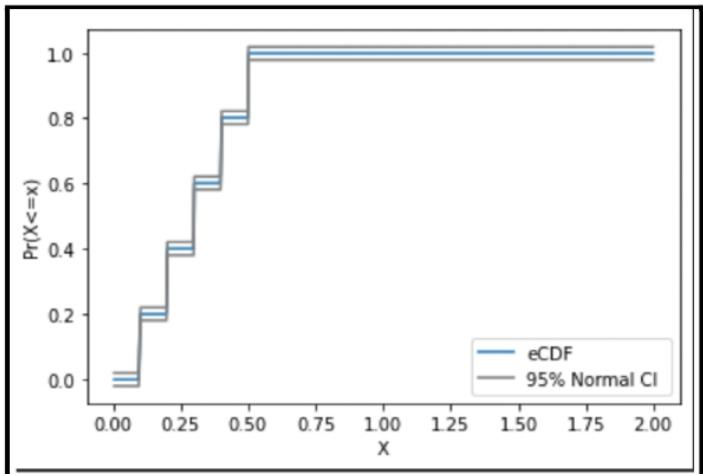


N=10, M=1000

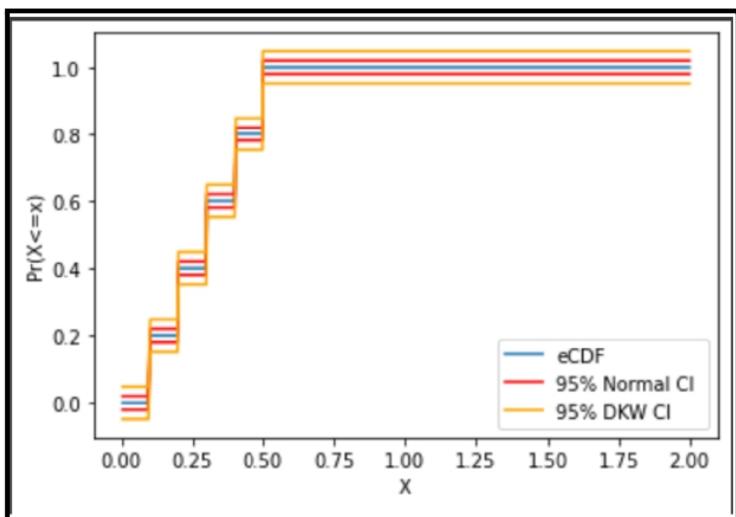


As the M value increases, the CDF becomes a straight line, the steps disappear as all the values are picked at least once in the M values.

E)



F)



After observing both the Intervals, We can conclude that the Normal-Based Confidence Intervals are tighter than compared to the DKW Confidence Intervals

5) Show plug-in estimator of the variance of x
 (a) is $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2$, where \bar{x}_n is
 the sample mean $\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i$

$$\begin{aligned}\hat{\sigma}^2 &= E[x^2] - (E[x])^2 \\ &= \sum_i x_i^2 p_\theta(x_i) - \left(\sum_i x_i p_\theta(x_i) \right)^2\end{aligned}$$

$$D \stackrel{i.i.d.}{=} \{x_1, x_2, \dots, x_n\} \quad \hat{P}_x(\alpha) = \begin{cases} \frac{1}{n} & \text{if } \alpha \in D \\ 0 & \text{otherwise} \end{cases}$$

Plug in estimate

$$\hat{\sigma}^2 = \sum_{\alpha \in D} \alpha^2 \hat{P}_x(\alpha) - \left(\sum_{\alpha \in D} \alpha_i \hat{P}_x(\alpha) \right)^2$$

$$\hat{\sigma}^2 = \sum_{i=1}^n (\alpha_i)^2 \left(\frac{1}{n} \right) - \left(\sum_{i=1}^n \alpha_i \left(\frac{1}{n} \right) \right)^2$$

$$= \frac{1}{n} \sum_{i=1}^n \alpha_i^2 - \cancel{\frac{1}{n^2} \sum_{i=1}^n \alpha_i}$$

[Given $\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i$]

$$= \frac{1}{n} \sum_{i=1}^n (x_i)^2 - \bar{x}_n^2 \rightarrow ①$$

R.H.S

$$\begin{aligned}\hat{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2 \\ &= \frac{1}{n} \sum_{i=1}^n (x_i^2 + (\bar{x}_n)^2 - 2x_i \bar{x}_n)\end{aligned}$$

$$D = \frac{1}{n} \sum_{i=1}^n x_i^2 + \frac{1}{n} \sum_{i=1}^n \bar{x}_n^2 - \frac{1}{n} (2) \sum_{i=1}^n x_i \bar{x}_n$$

\bar{x}_n is a constant

$$= \frac{1}{n} \sum_{i=1}^n x_i^2 + \frac{1}{n} \bar{x}_n^2 (D) - \frac{2}{n} (\bar{x}_n) \sum_{i=1}^n x_i$$

$$= \frac{1}{n} \sum_{i=1}^n x_i^2 + \bar{x}_n^2 - 2\bar{x}_n \sum_{i=1}^n \frac{x_i}{n}$$

$$= \frac{1}{n} \sum_{i=1}^n x_i^2 + \bar{x}_n^2 - 2\bar{x}_n (\bar{x}_n) \quad \left[\text{Given } \bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i \right]$$

$$\Rightarrow \frac{1}{n} \sum_{i=1}^n x_i^2 + \bar{x}_n^2 - 2\bar{x}_n (\bar{x}_n)$$

$$= \frac{1}{n} \sum_{i=1}^n x_i^2 - \bar{x}_n^2 \rightarrow ②$$

$$① = ②$$

$$\therefore \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2$$

$$5^{\textcircled{b}} \quad \text{bias}(\hat{\sigma}^2) = E[\hat{\sigma}^2] - \sigma^2$$

$$\begin{aligned} E[\hat{\sigma}^2] &= E\left[\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2\right] \\ &= E\left[\frac{1}{n} \left(\sum_{i=1}^n (x_i^2 + \bar{x}_n^2 - 2x_i\bar{x}_n) \right)\right] \\ &= \frac{1}{n} E\left[\sum_{i=1}^n x_i^2 + \sum_{i=1}^n \bar{x}_n^2 - 2\bar{x}_n \sum_{i=1}^n x_i \right] \\ &\stackrel{LOE}{=} \frac{1}{n} E\left[\sum_{i=1}^n x_i^2 + \bar{x}_n^2(n) - 2\bar{x}_n(n)(\bar{x}_n) \right] \\ &= \frac{1}{n} E\left[\sum_{i=1}^n x_i^2 - n\bar{x}_n^2 \right] \\ &= \frac{1}{n} \left(E\left[\sum_{i=1}^n x_i^2 \right] - E[n\bar{x}_n^2] \right) \quad - ① \\ &\stackrel{LOE}{=} \frac{1}{n} \left(E\left[\sum_{i=1}^n x_i^2 \right] - E[n\bar{x}_n^2] \right) \end{aligned}$$

$$\begin{aligned} \cancel{E[x_n^2]} &= \cancel{\text{Var}[x_n]} + (E[x_n])^2 \\ E[x^2] &= \text{Var}[x] + (E[x])^2 \end{aligned}$$

Consider

$$\begin{aligned} E[\bar{x}_n^2] &= \text{Var}[\bar{x}_n] + (E[\bar{x}_n])^2 \\ &= \text{Var}\left[\frac{1}{n} \sum_{i=1}^n x_i\right] + \left(E\left[\frac{1}{n} \sum_{i=1}^n x_i\right]\right)^2 \\ &\stackrel{LOV}{=} \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i) + \left(\frac{1}{n} \sum_{i=1}^n E[x_i]\right)^2 \end{aligned}$$

$$\stackrel{i.i.d}{=} \frac{1}{n^2} n \text{Var}[x] + \left(\frac{1}{n} \sum x_i E[x] \right)^2$$

$$E[\bar{x}_n^2] = \frac{1}{n} \text{Var}[x] + (E[x])^2 \quad - \textcircled{2}$$

Substitute $\textcircled{2}$ in $\textcircled{1}$

$$= \frac{1}{n} \left(\sum_{i=1}^n E[x_i^2] - n E[\bar{x}_n^2] \right)$$

$$= \left(\frac{1}{n} \sum_{i=1}^n E[x_i^2] - n \left(\frac{1}{n} \text{Var}[x] + (E[x])^2 \right) \right)$$

$$\stackrel{i.i.d}{=} \frac{1}{n} \sum x_i E[x] - \text{Var}[x] + (E[x])^2$$

$$\stackrel{i.i.d}{=} \frac{1}{n} \sum x_i E[x^2] - \frac{\text{Var}[x]}{n} + (E[x])^2$$

$$= E[x^2] - (E[x])^2 - \frac{\text{Var}[x]}{n}$$

$\rightarrow \textcircled{3}$

$$\therefore E[\hat{\sigma}^2] = \sigma^2 - \frac{\sigma^2}{n}$$

$$\begin{aligned} \text{bias}(\hat{\sigma}^2) &= E[\hat{\sigma}^2] - \sigma^2 \\ &= \sigma^2 - \frac{\sigma^2}{n} - \sigma^2 \end{aligned}$$

$$= -\frac{\sigma^2}{n}$$

$$\therefore \text{bias}(\hat{\sigma}^2) = -\frac{\sigma^2}{n}$$

Hence proved

$$5(c) \text{ Kurt}[X] = \frac{E[(X-\mu)^4]}{\sigma^4}$$

Let $\hat{\sigma}_2, \hat{\mu}$ be the plugin estimator for σ^2, μ

From 5(a) we know that

$$\hat{\sigma}_2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2 \quad - \textcircled{1}$$

$$\hat{\mu} = \bar{x}_n$$

$$[E[X^i] = \sum_{i=0}^n x^i p(x)]$$

$$\text{Consider } E[(X-\mu)^4]$$

$$\begin{aligned}
 &= \sum_{i=1}^n (x_i - \mu)^4 \cdot p(x_i) \\
 &\stackrel{\text{plugin estimator}}{=} \sum_{i=1}^n (x_i - \hat{\mu})^4 \cdot p(x_i) \quad \left[\hat{p}(x_i) = \frac{1}{n} \right] \\
 &= \sum_{i=1}^n (x_i - \hat{\mu})^4 \left(\frac{1}{n} \right) \\
 &= \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^4
 \end{aligned} \rightarrow \textcircled{2}$$

From eq ①

$$\hat{\sigma}_4 = \frac{1}{n^2} \left(\sum_i (x_i - \bar{x}_n)^2 \right)^2 \quad - \textcircled{3}$$

From eq ② & ③

$$\text{Kurt}[\hat{x}] = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^4}{\left(\frac{1}{n^2} \left(\sum_{i=1}^n (x_i - \bar{x}_n)^2 \right)^2 \right)^2}$$

$$= n \frac{\sum_i (x_i - \bar{x}_n)^4}{\left(\sum_i (x_i - \bar{x}_n)^2 \right)^2}$$

$$5(d) \quad \rho = \frac{E[XY] - E[X]E[Y]}{\sigma_X \sigma_Y}$$

$$\sigma_X^2 = E[X^2] - (E[X])^2$$

$$\sigma_Y^2 = E[Y^2] - (E[Y])^2$$

$(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)$

n i.i.d. $\{(x_i, y_i)\}, (x_1, y_1), (x_2, y_2), (x_3, y_3)$

D: $\{x_i, y_i\} \in \{(x_i, y_i)\}$

$$\text{ePMF: } \begin{cases} y_i & \text{if } i=j \\ 0 & \text{otherwise} \end{cases} \rightarrow \hat{P}(x=x_i \cap y=y_i)$$

$$\rho = \frac{\sum_{x \in D} \sum_{y \in D} P(x=x \cap y=y) - \left(\sum_{x \in D} P(x=x) \right) \left(\sum_{y \in D} y P(y=y) \right)}{\sqrt{\left(\sum_{x \in D} x^2 P(x=x) - \left(\sum_{x \in D} x P(x=x) \right)^2 \right) \left(\sum_{y \in D} y^2 P(y=y) - \left(\sum_{y \in D} y P(y=y) \right)^2 \right)}}$$

$$\hat{\rho} = \frac{\sum_{x \in D} \sum_{y \in D} xy \hat{P}(x=x \cap y=y) - \left(\sum_{x \in D} x \hat{P}_x(x) \right) \left(\sum_{y \in D} y \hat{P}_y(y) \right)}{\sqrt{\left(\sum_{x \in D} x^2 \hat{P}_x(x) - \left(\sum_{x \in D} x \hat{P}_x(x) \right)^2 \right) \left(\sum_{y \in D} y^2 \hat{P}_y(y) - \left(\sum_{y \in D} y \hat{P}_y(y) \right)^2 \right)}}$$

$$= \frac{1}{n} \sum_{i=1}^n x_i y_i - \frac{1}{n^2} \left(\sum_{i=1}^n x_i \right) \left(\sum_{i=1}^n y_i \right)$$

$$= \sqrt{\left(\frac{1}{n} \sum_{i=1}^n x_i^2 - \frac{1}{n^2} \left(\sum_{i=1}^n x_i \right)^2 \right) \left(\frac{1}{n} \sum_{i=1}^n y_i^2 - \frac{1}{n^2} \left(\sum_{i=1}^n y_i \right)^2 \right)}$$

$$\hat{R} = \frac{n \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{\sqrt{(\sum_{i=1}^n x_i^2 - (\sum x_i)^2)(n \sum y_i^2 - (\sum y_i)^2)}}$$

⑥

Properties of estimators

~~(a)~~ Given $\hat{\theta} = \frac{1}{n} \sum_{i=1}^n x_i$ where x_i are i.i.d. \sim Poisson(θ)

i) bias = $E(\hat{\theta}) - \theta$

$$\begin{aligned} E(\hat{\theta}) &= E\left[\frac{1}{n} \sum_{i=1}^n x_i\right] \\ &= \frac{1}{n} E\left(\sum_{i=1}^n x_i\right) \stackrel{\text{LOE}}{=} \frac{1}{n} \sum_{i=1}^n E[x_i] \\ &\stackrel{\text{i.i.d.}}{=} \frac{1}{n} n E[x] = E[x] \end{aligned}$$

$$E[\hat{\theta}] = E[x]$$

$$\begin{aligned} \text{bias} &= E[\hat{\theta}] - \theta = E[x] - \theta \\ x \sim \text{Poisson}(\theta) &= \frac{\theta e^{-\theta}}{x!} \end{aligned}$$

W.K.T
$$\boxed{E[x] = \theta}$$

$$\begin{aligned} \text{bias} &= E[x] - \theta = \theta - \theta \\ &= 0 \end{aligned}$$

$$\text{ii) } SE = \sqrt{\text{Var}(\hat{\theta})}$$

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

$$\text{Var}(\hat{\theta}) = \text{Var}\left(\frac{1}{n} \sum_i x_i\right)$$

$$= \frac{1}{n^2} \text{Var}(\sum x_i) \stackrel{\text{Loy}}{=} \frac{1}{n^2} \sum \text{Var}(x_i)$$

($\because x_i$'s are iid)

$$= \frac{1}{n^2} \cdot n \cdot \text{Var}(x)$$

$$= \frac{1}{n} \text{Var}(x)$$

$$x \sim \text{Poisson}(\theta) = \frac{\theta^x e^{-\theta}}{x!}$$

[For Poisson distribution
Variance = θ]

$$\Rightarrow \frac{1}{n} \text{Var}(x) = \frac{\theta}{n}$$

$$SE = \sqrt{\text{Var}(\hat{\theta})} = \sqrt{\frac{\theta}{n}}$$

$$\text{i)} \quad \text{MSE} = \text{bias}^2(\hat{\theta}) + \text{Var}(\hat{\theta})$$

From i. & ii.

$$= \theta^2 + \frac{\theta}{n}$$

$$\boxed{\text{MSE} = \frac{\theta}{n}}$$

$$7) \text{ Given } \hat{\theta} = \hat{F}_n(b) - \hat{F}_n(a)$$

$$\theta = F(b) - F(a)$$

(a) $\hat{s}\hat{e}(\hat{\theta})$

$$\text{See } \hat{\theta} = \hat{F}_n(b) - \hat{F}_n(a) \Rightarrow \frac{1}{n} \sum_{i=1}^n I(x_i \leq b) - \frac{1}{n} \sum_{i=1}^n I(x_i \leq a)$$

$$s\hat{e}(\hat{\theta}) = \sqrt{\text{Var}(\hat{\theta})}$$

$$\text{Var}(\hat{\theta}) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n I(x_i \leq b) - \frac{1}{n} \sum_{i=1}^n I(x_i \leq a)\right)$$

$$= \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n I(x_i \leq b) - \sum_{i=1}^n I(x_i \leq a)\right)$$

$$= \frac{n}{n^2} \text{Var}(I(x \leq b) - I(x \leq a))$$

The distribution is in the form of binomial distribution
 [W.K.T Variance of indicator distribution is $P(1-P)$]

[W.K.T Variance of indicator distribution is $P(1-P)$]

$$= \frac{1}{n} \text{Var}(I(x \leq b) - I(x \leq a))$$

$$= \frac{1}{n} (P_I(x \leq b) - P_I(x \leq a)) (1 - (P_I(x \leq b) - P_I(x \leq a)))$$

$$= \frac{1}{n} (P_I(x \leq b) - P_I(x \leq a)) (1 - (F(b) - F(a)))$$

$$= \frac{1}{n} (F(b) - F(a))$$

$$= \frac{\theta(1-\theta)}{n}$$

$$SE[\hat{\theta}] = \sqrt{Var[\hat{\theta}]}$$

$$= \sqrt{\frac{\theta(1-\theta)}{n}}$$

(b) Find an approximate $(1-\alpha)$ CI for θ

$$\theta = F(b) - F(a) \text{ true value}$$

$$\hat{\theta} = \hat{F}(b) - \hat{F}(a) \rightarrow eCDF$$

w.k.t If $\hat{\theta} \sim \text{Normal}(\theta, se)$ then a $(1-\alpha)$ CI for θ is

$$(\hat{\theta} - Z_{\alpha/2} se, \hat{\theta} + Z_{\alpha/2} se)$$

We need to show that $\hat{\theta}$ is a normal distribution

$$\hat{\theta} = \hat{F}_n(b) - \hat{F}_n(a) \rightarrow ①$$

$$= \frac{1}{n} \sum_{i=1}^n I(x_i \leq b) - \frac{1}{n} \sum_{i=1}^n I(x_i \leq a)$$

$I(x_i \leq b)$ is the indicator of event and a Bernoulli random variable with mean P & variance as $P(1-P)$

$$\text{From } ①$$

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n I(x_i \leq b) - \frac{1}{n} \sum_{i=1}^n I(x_i \leq a)$$

$$\hat{\theta} = I(x \leq b) - I(x \leq a)$$

Using CLT, it can be approximated to a normal distribution with

$$\mu = E[I(X \leq b)] - E[I(X \leq a)]$$

$$= E[I(X \leq b)] - E[I(X \leq a)]$$

$$= P_f(X \leq b) - P_f(X \leq a)$$

$$= F(b) - F(a) = \theta$$

$$\text{From (a) Variance} = \frac{(F(b) - F(a))(1 - (F(b) - F(a)))}{n}$$

$$= \theta \frac{(1-\theta)}{n}$$

$$se = \sqrt{\frac{\theta(1-\theta)}{n}}$$

\therefore An approximate 1-d CI for θ is $\hat{\theta} \pm z_{\alpha/2} se$

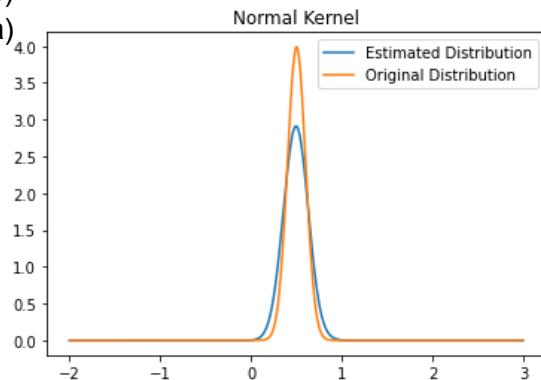
$$= \hat{\theta} \pm z_{\alpha/2} \sqrt{\frac{\theta(1-\theta)}{n}}$$

since θ is unknown in the CI, we will get estimated CI by replacing θ with $\hat{\theta}$

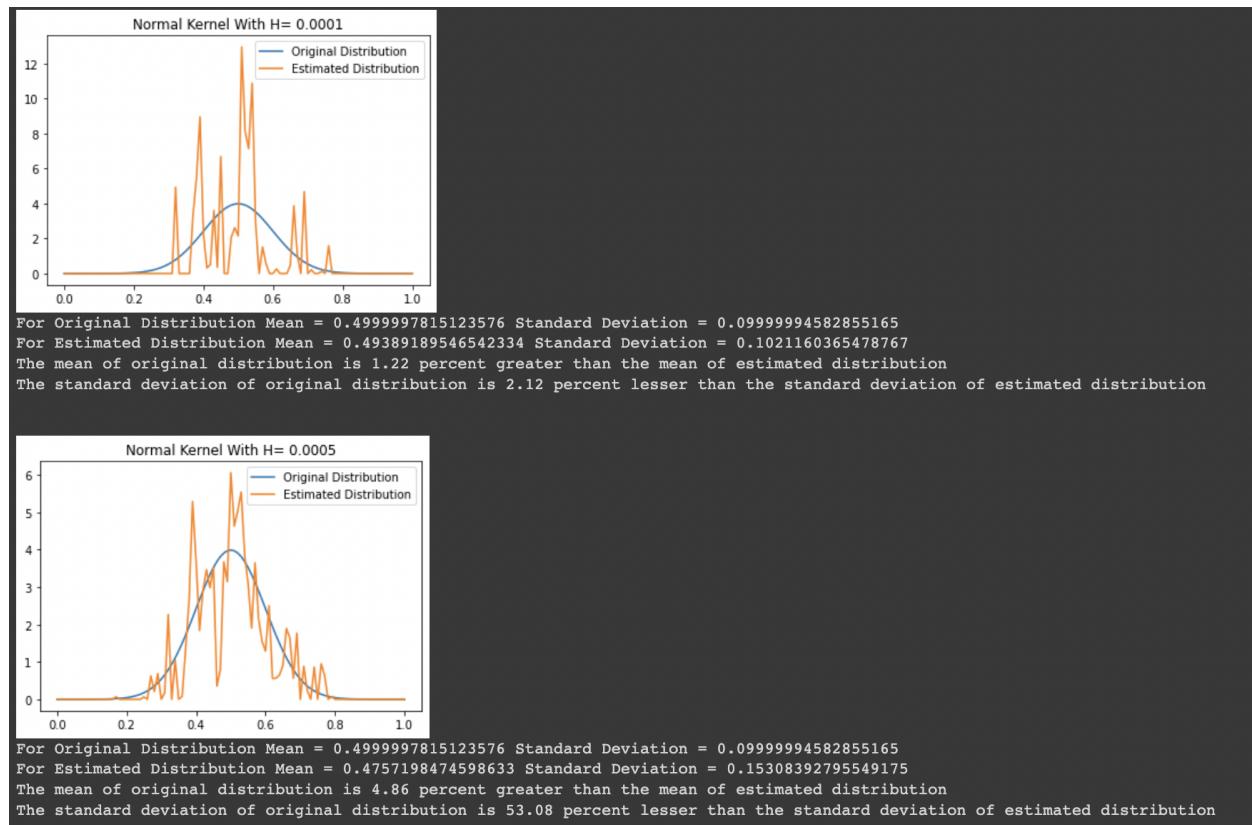
$$\hat{C.I} = \hat{\theta} \pm z_{\alpha/2} \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}}$$

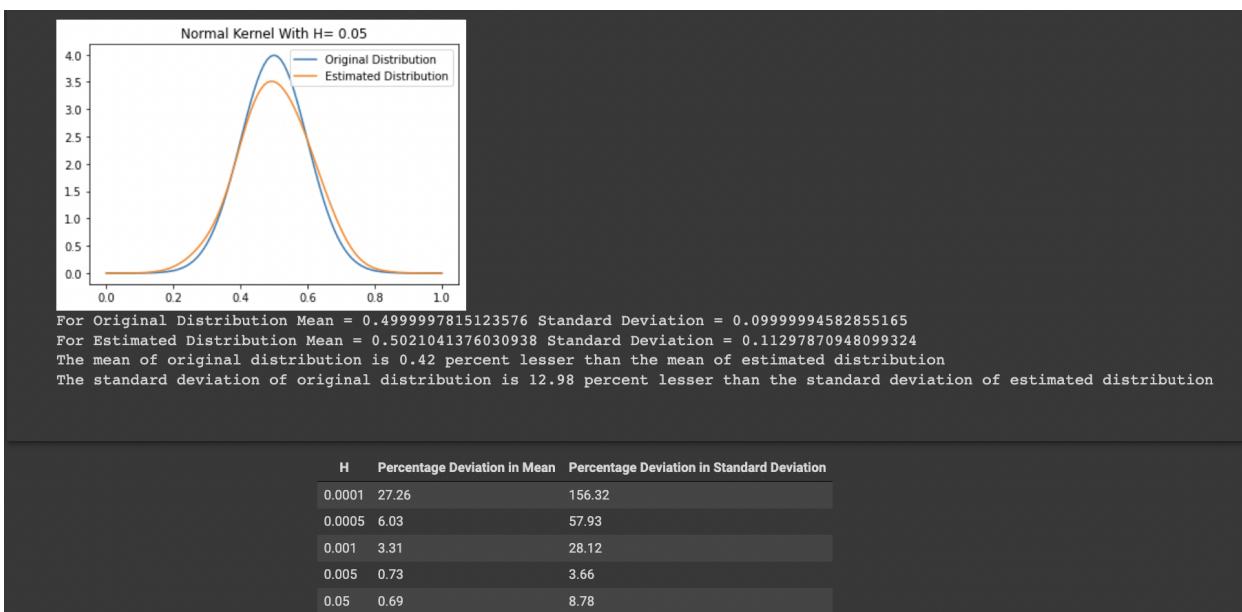
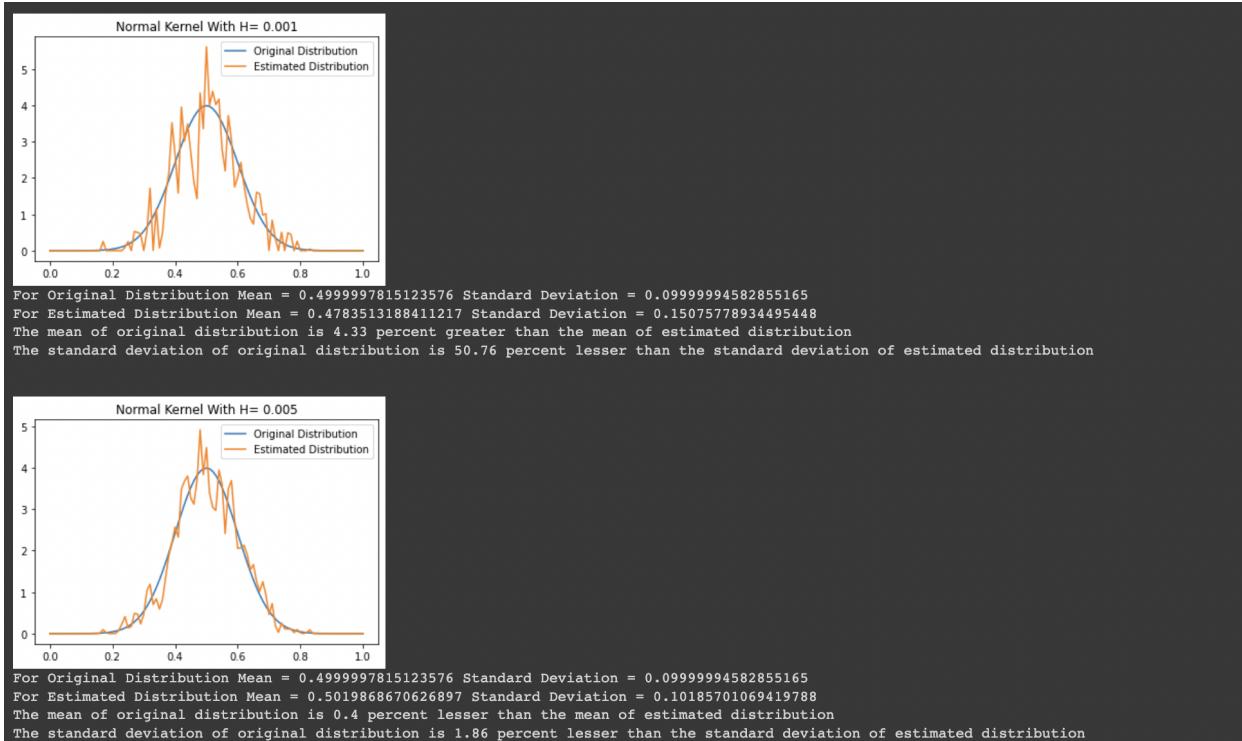
8)

a)



b)

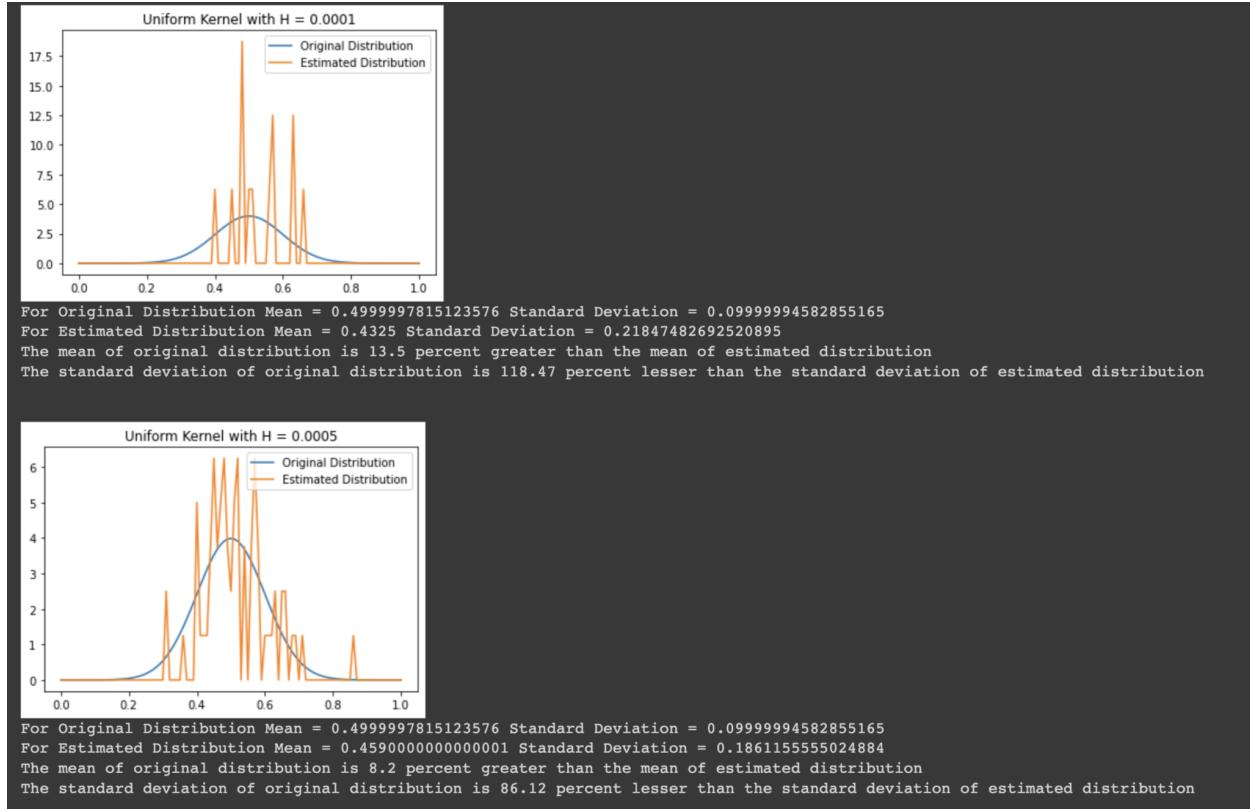


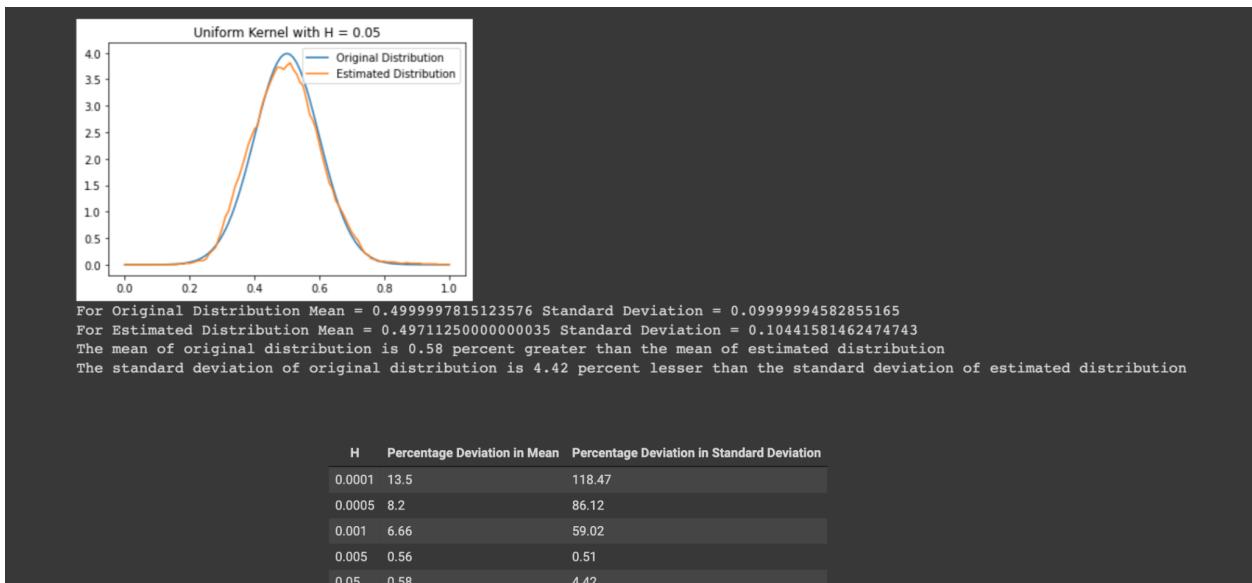
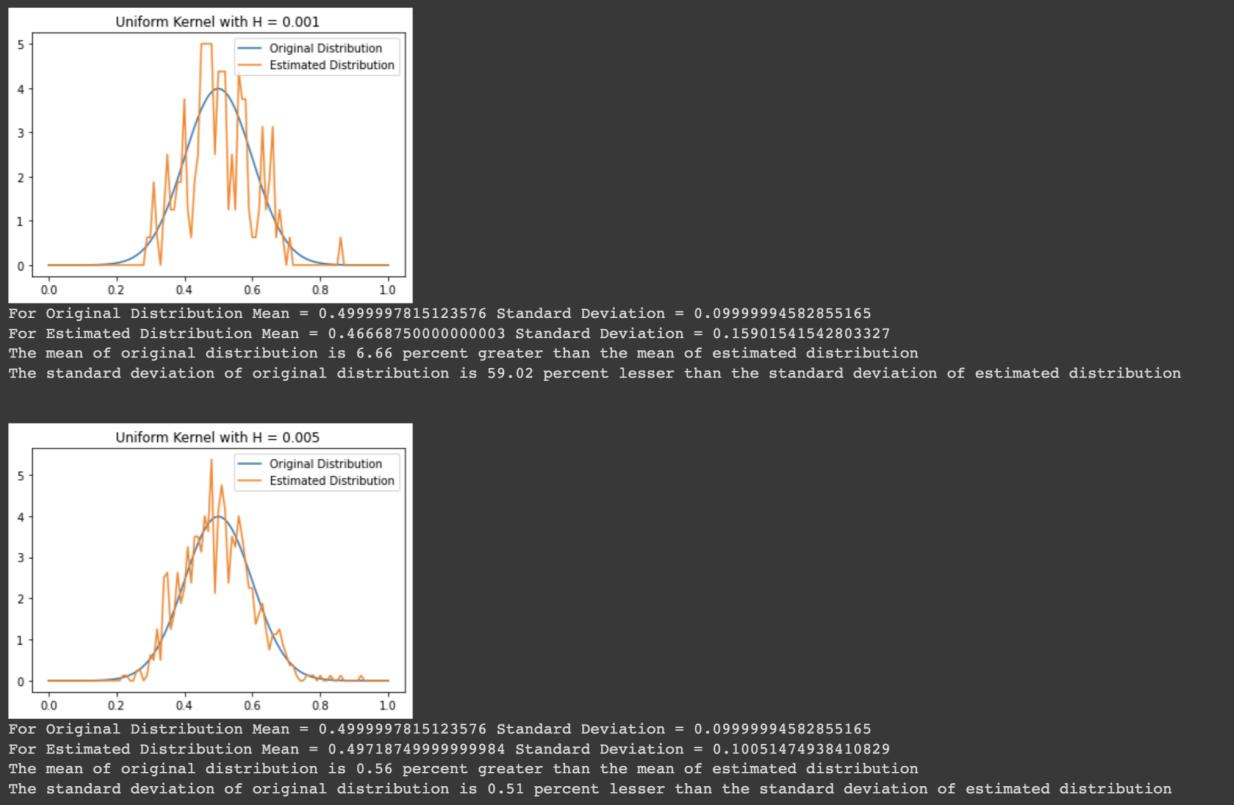


Based on the observation of above plots the H value of 0.05 looks like performing best.

And the deviations from original mean and variance are least for the H value of 0.005

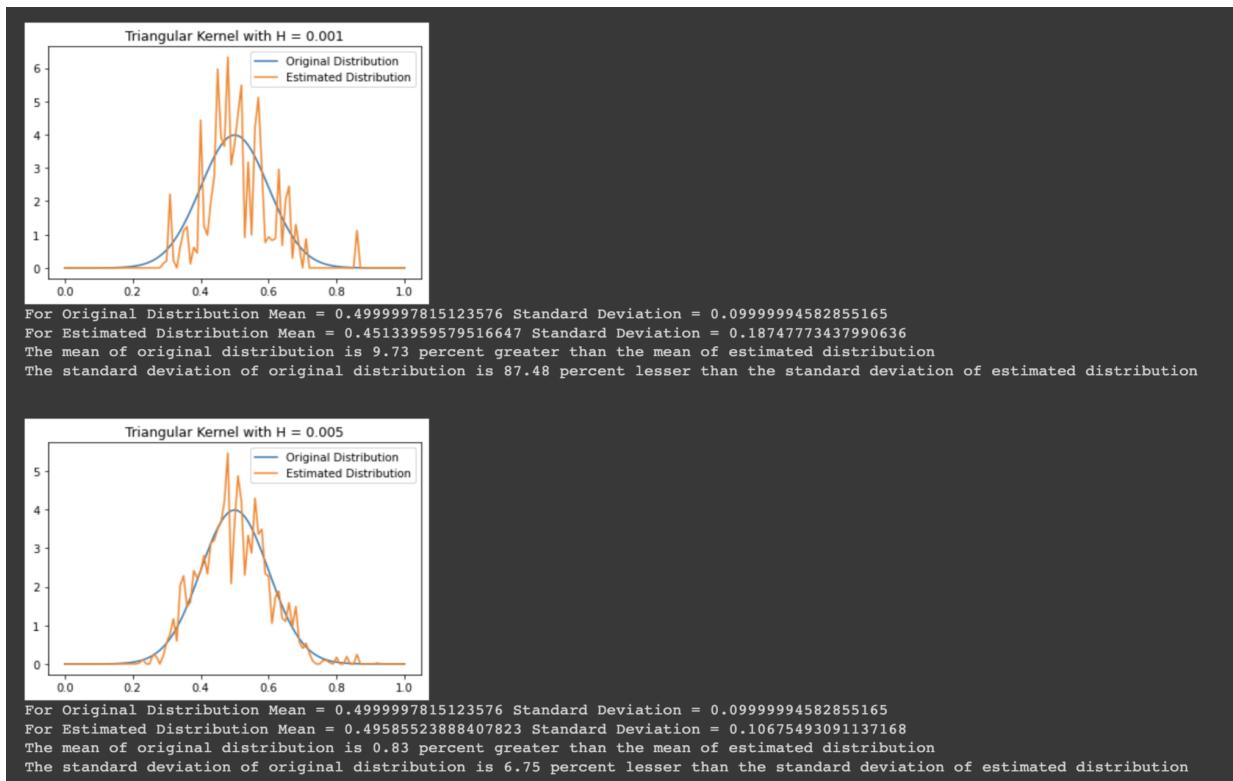
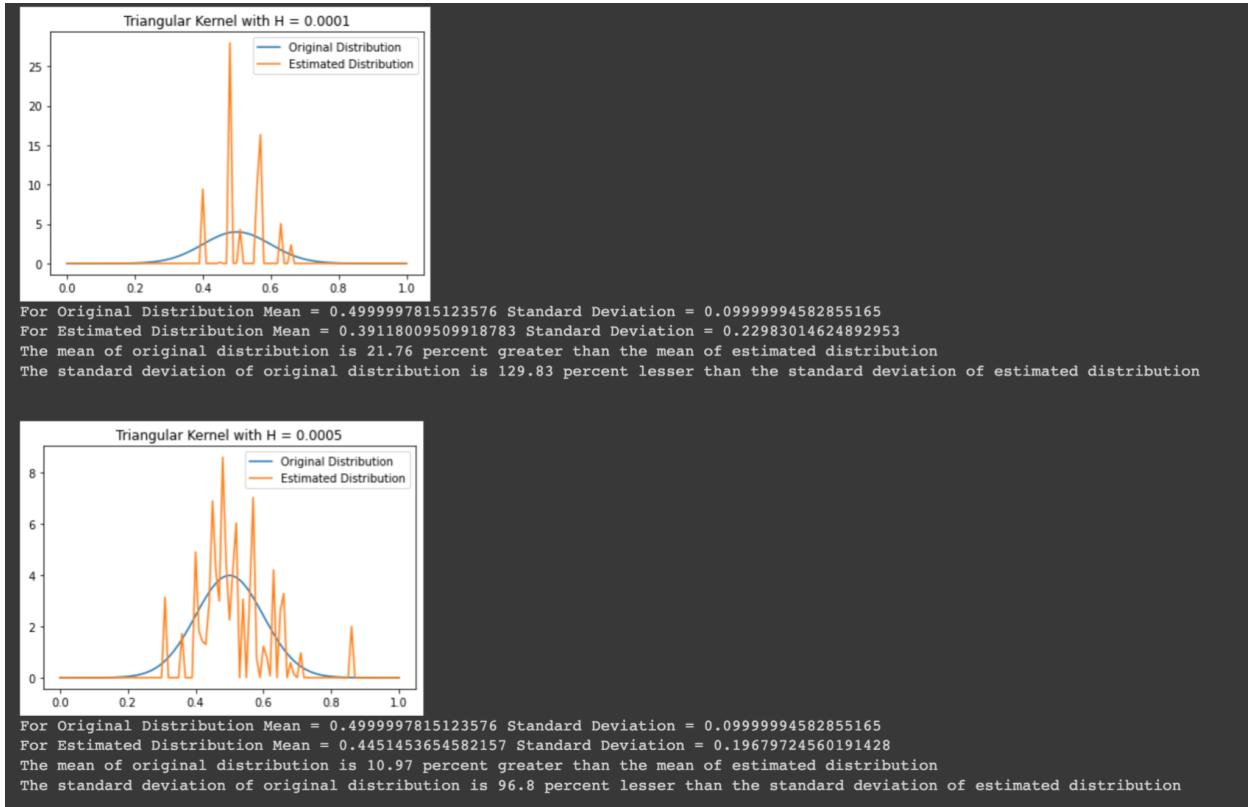
c)

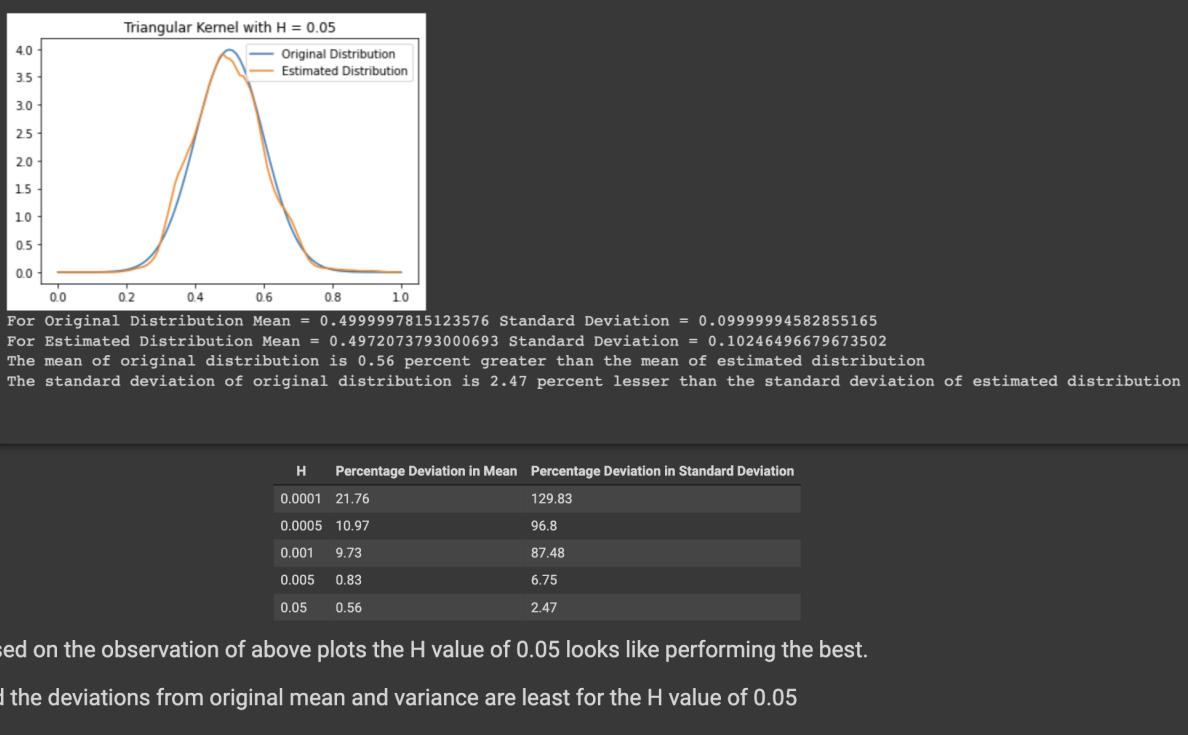




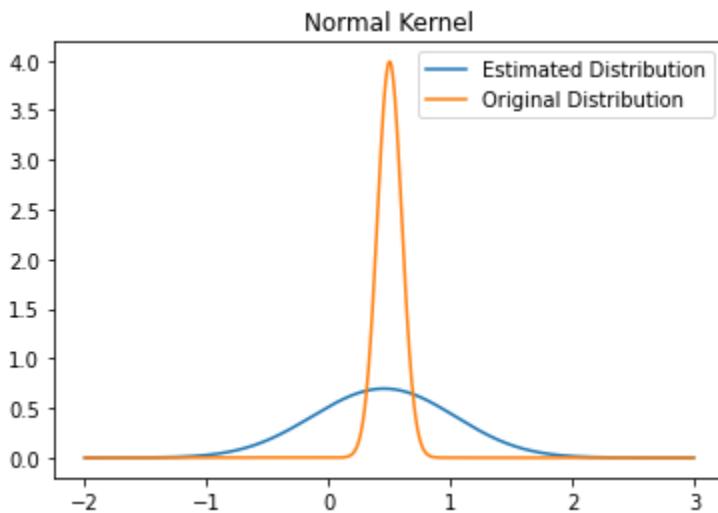
Based on the observation of above plots the H value of 0.05 looks like performing the best.

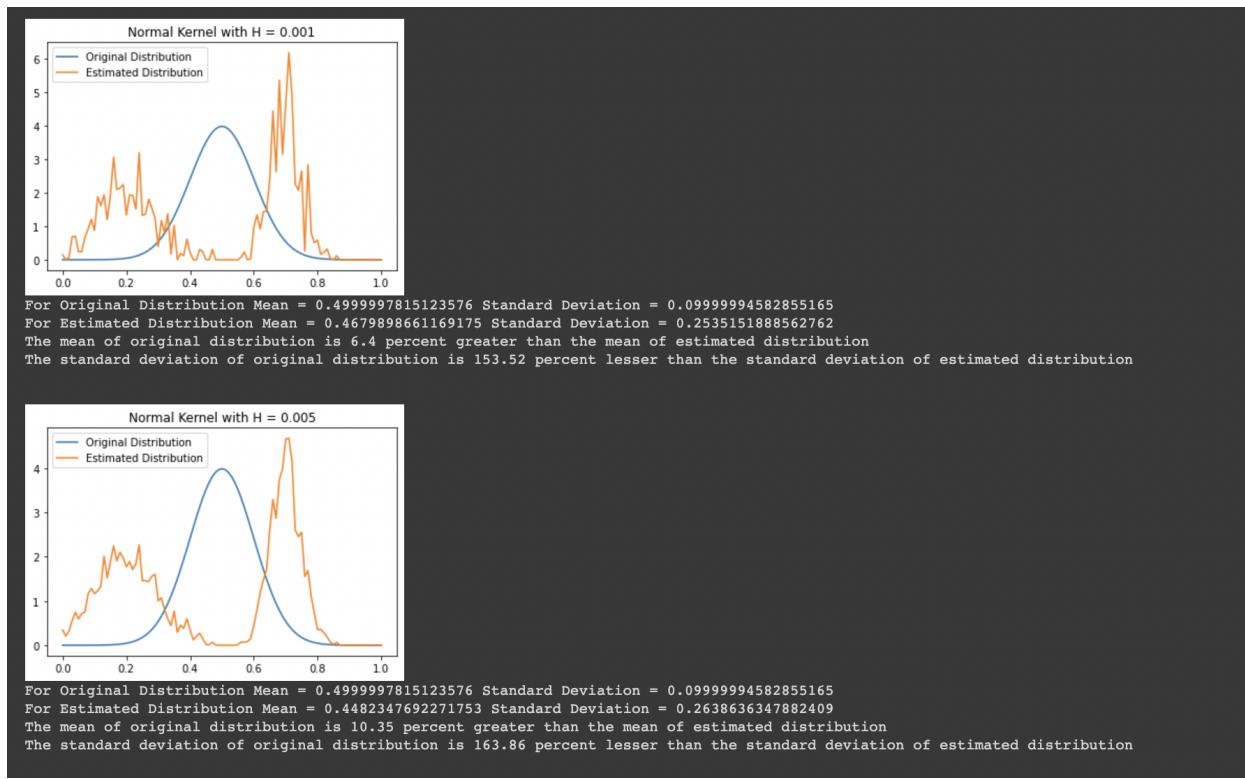
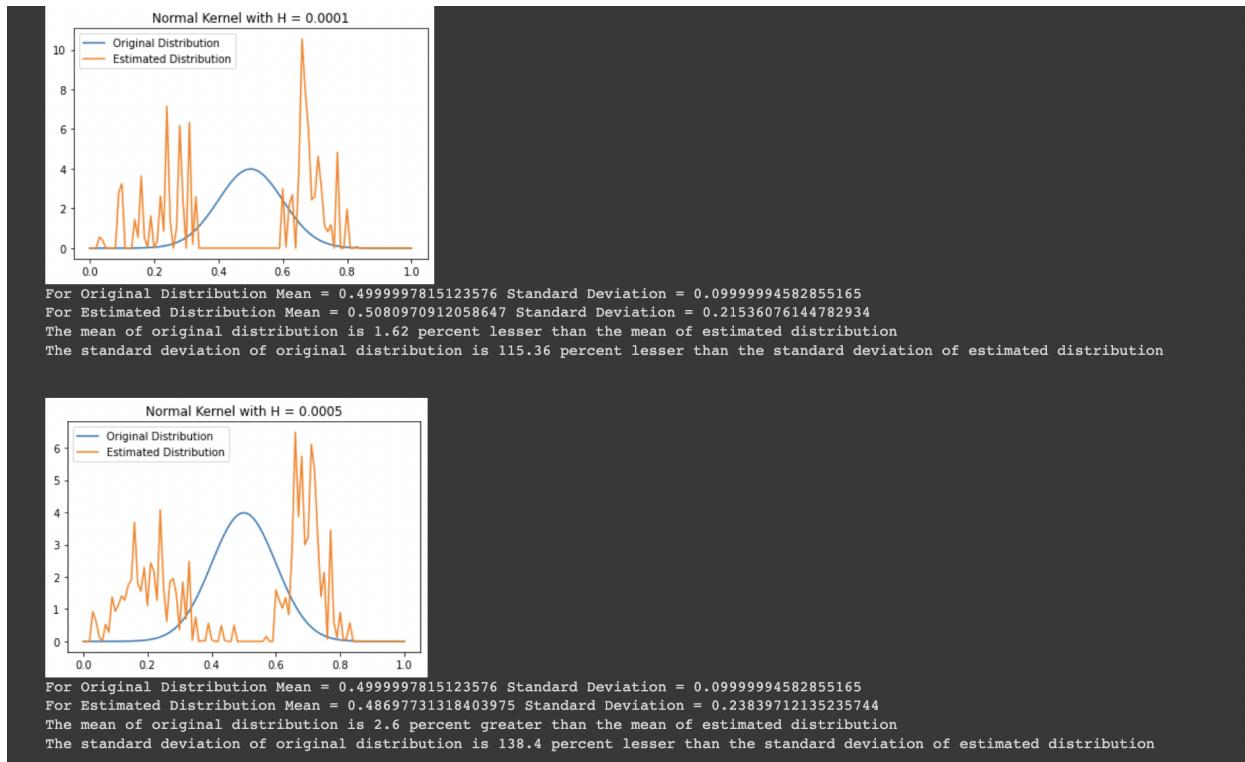
And the deviations from original mean and variance are least for the H value of 0.005

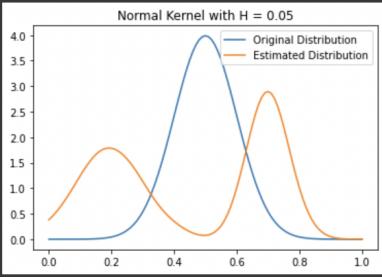




d)



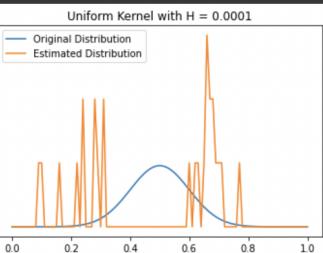




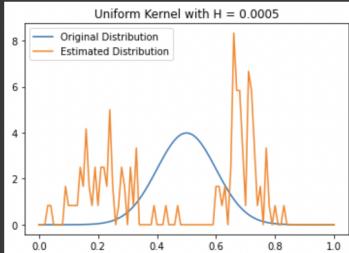
For Original Distribution Mean = 0.4999997815123576 Standard Deviation = 0.09999994582855165
 For Estimated Distribution Mean = 0.4485429342716778 Standard Deviation = 0.26778918892667736
 The mean of original distribution is 10.29 percent greater than the mean of estimated distribution
 The standard deviation of original distribution is 167.79 percent lesser than the standard deviation of estimated distribution

H	Percentage Deviation in Mean	Percentage Deviation in Standard Deviation
0.0001	1.62	115.36
0.0005	2.6	138.4
0.001	6.4	153.52
0.005	10.35	163.86
0.05	10.29	167.79

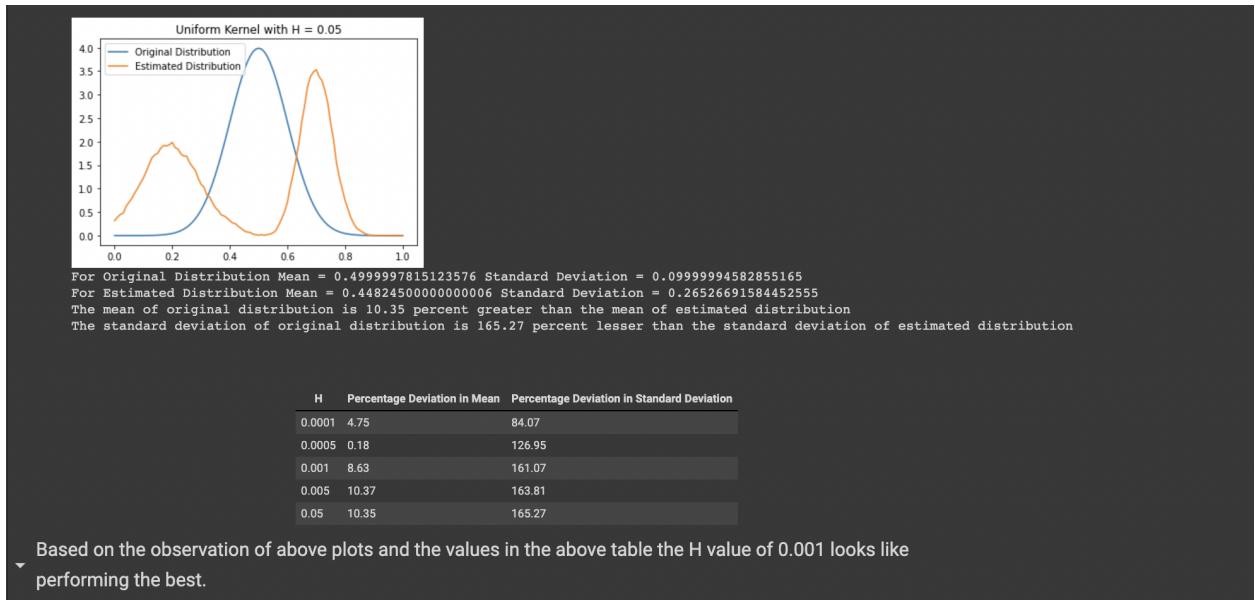
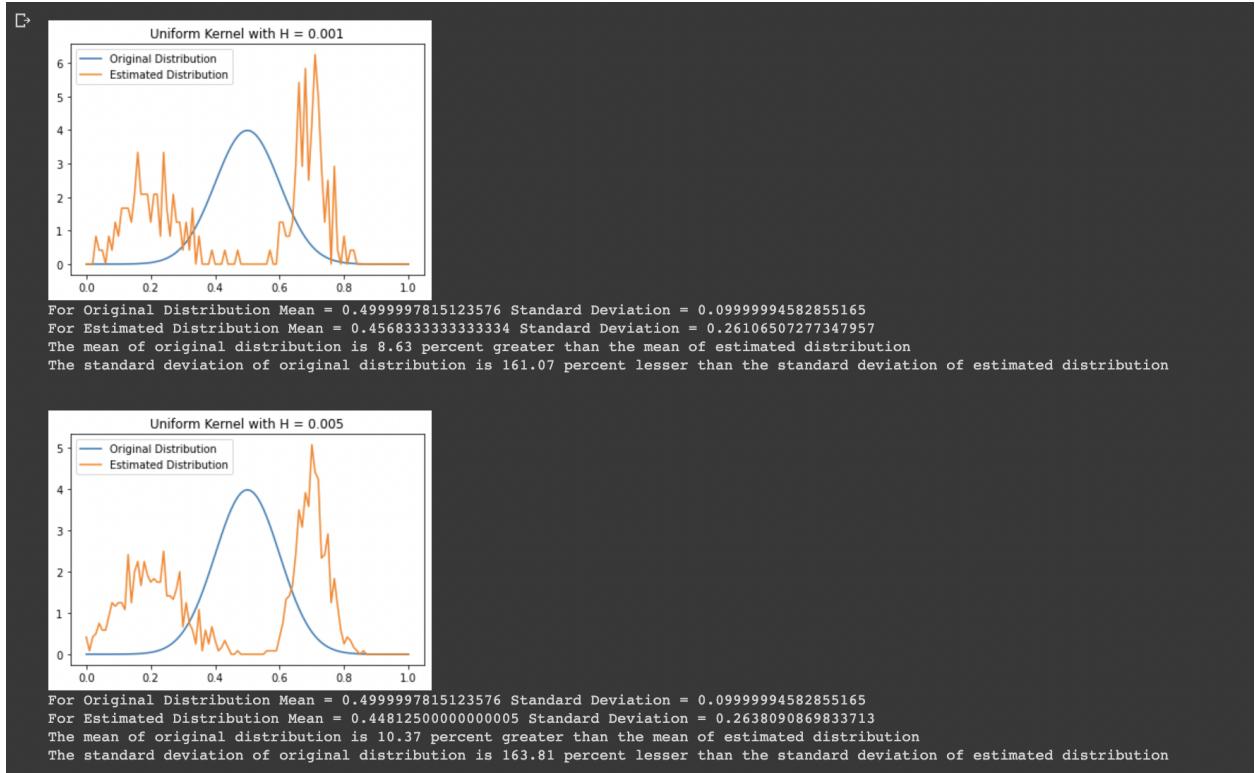
Based on the observation of above plots and the values in the above table the H value of 0.0001 looks like performing the best.

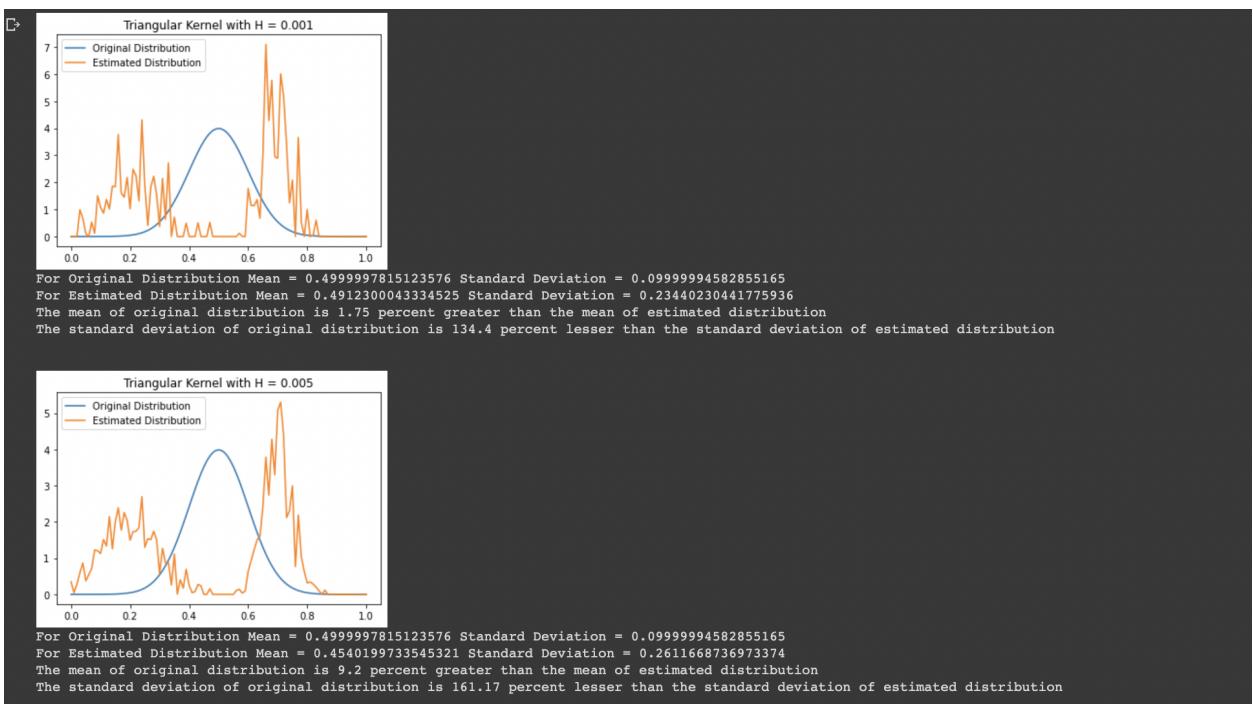
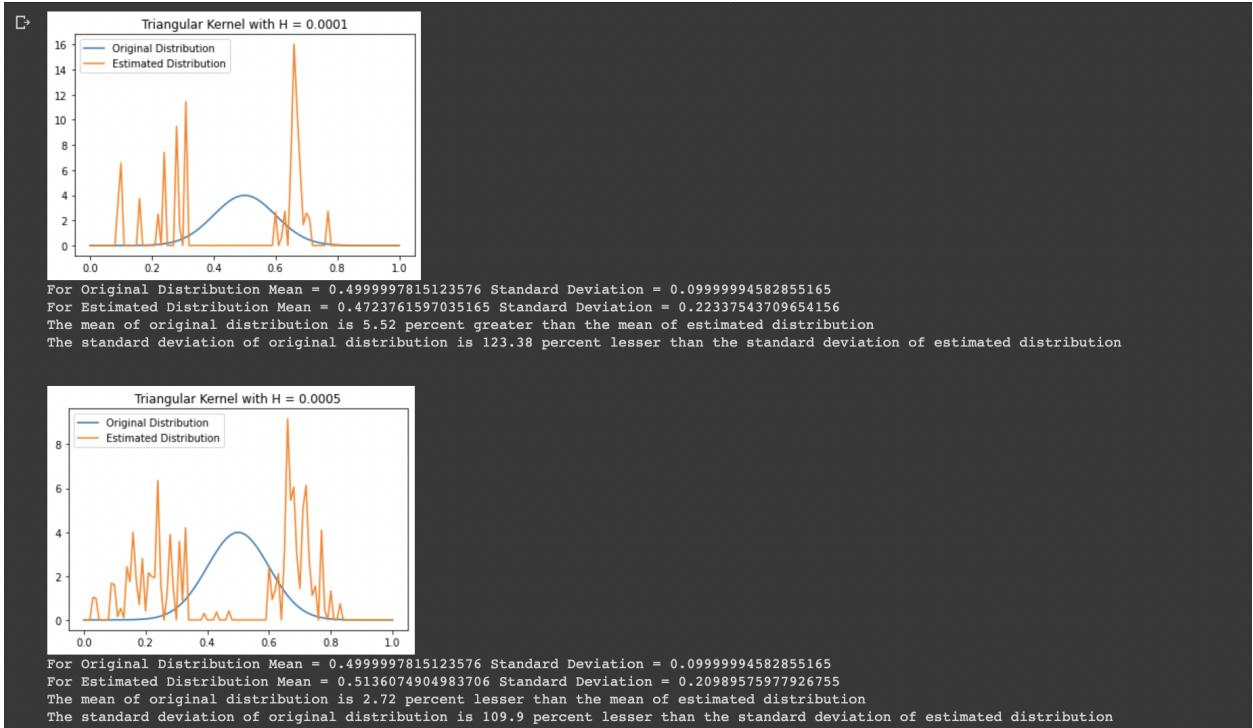


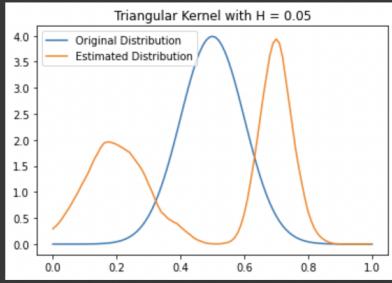
For Original Distribution Mean = 0.4999997815123576 Standard Deviation = 0.09999994582855165
 For Estimated Distribution Mean = 0.52375 Standard Deviation = 0.1840700161170562
 The mean of original distribution is 4.75 percent lesser than the mean of estimated distribution
 The standard deviation of original distribution is 84.07 percent lesser than the standard deviation of estimated distribution



For Original Distribution Mean = 0.4999997815123576 Standard Deviation = 0.09999994582855165
 For Estimated Distribution Mean = 0.4990833333333335 Standard Deviation = 0.22695078700507318
 The mean of original distribution is 0.18 percent greater than the mean of estimated distribution
 The standard deviation of original distribution is 126.95 percent lesser than the standard deviation of estimated distribution







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For Original Distribution Mean = 0.4999997815123576 Standard Deviation = 0.09999994582855165
For Estimated Distribution Mean = 0.4481913939074269 Standard Deviation = 0.26454555398348106
The mean of original distribution is 10.36 percent greater than the mean of estimated distribution
The standard deviation of original distribution is 164.55 percent lesser than the standard deviation of estimated distribution

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H	Percentage Deviation in Mean	Percentage Deviation in Standard Deviation
0.0001	5.52	123.38
0.0005	2.72	109.9
0.001	1.75	134.4
0.005	9.2	161.17
0.05	10.36	164.55

- Based on the observation of above plots and the values in the above table the H value of 0.001 looks like performing the best.

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