

Remarks about α -TM:-

$$\alpha \in [0, \frac{1}{2}) .$$

→ NOT robust
against the
outliers.

- i) Already mentioned, $\alpha = 0$, α -TM = Sample mean outliers.
 $\alpha \rightarrow \frac{1}{2}$, α -TM → Sample median
↳ Robust.

It gives an impression that, the tuning parameter " α " controls the robustness against the outliers.

- ii) The choice of α is an issue of research.
iii) α -TM is also equivariant under arbitrary affine transformation.

Remark:-

Sample mean, Sample median & Sample α -TM all of them are asymptotically normal after normalization by \sqrt{n} .

Measure of spreadness:-

i) Variance :- $X = \{x_1, \dots, x_n\}$

Sample variance = $\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2$, where $\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i$.

Sample standard deviation = $\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2}$

A few other measures:-

Mean absolute deviation about mean

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

Remark:-

All these ~~as~~ measures are NOT robust.

Robust version of measure of 'spreadness':-

Median absolute deviation about median

$X = \{x_1, \dots, x_n\}$, It is defined as $\text{Med} \left\{ \left| x_i - \text{Median}(x_i) \right| \right\}$.

Remark:- It is robust against the outliers.

Remark:- All these measure are invariant under

location transformation ($x \rightarrow x + c$) but equivariant

under scale transformation ($x \rightarrow ax$).

A few more order statistic based measure:-

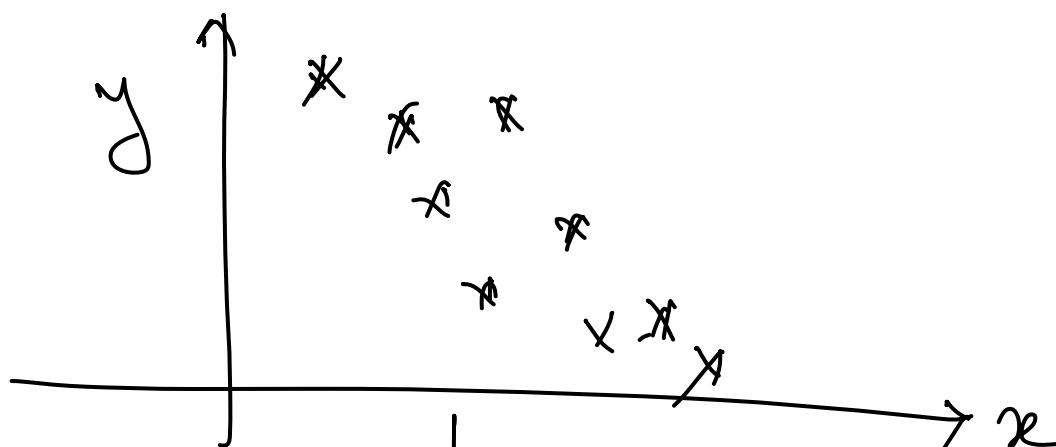
$$\text{Range} = x_{(n)} - x_{(1)}$$

$$\text{Interquartile range} = x_{[0.75n]} - x_{[0.25n]}, \text{ where}$$

n is the sample size.

Analysis of data based on graphical device:-

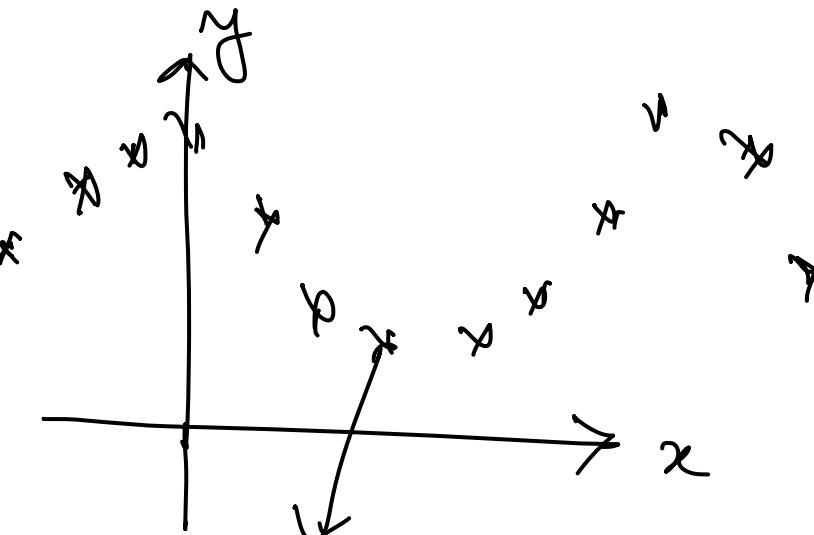
i) Scatter plot (Plot on 2-dimensional plane).



Monotonic
association



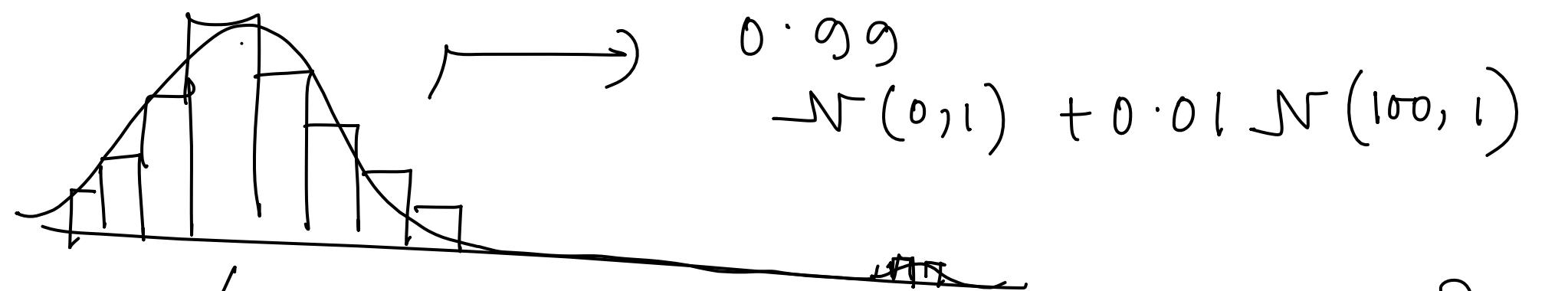
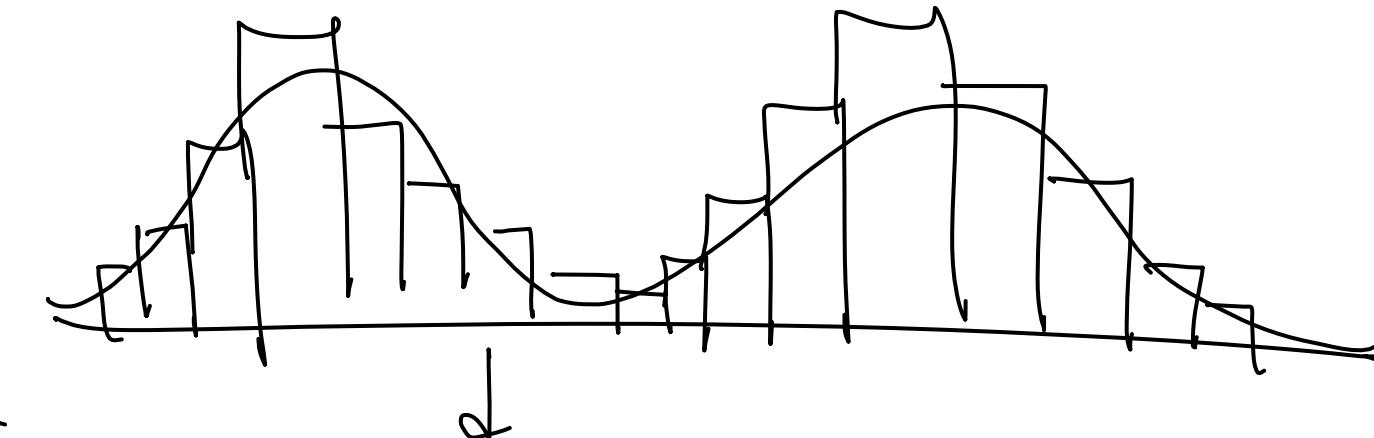
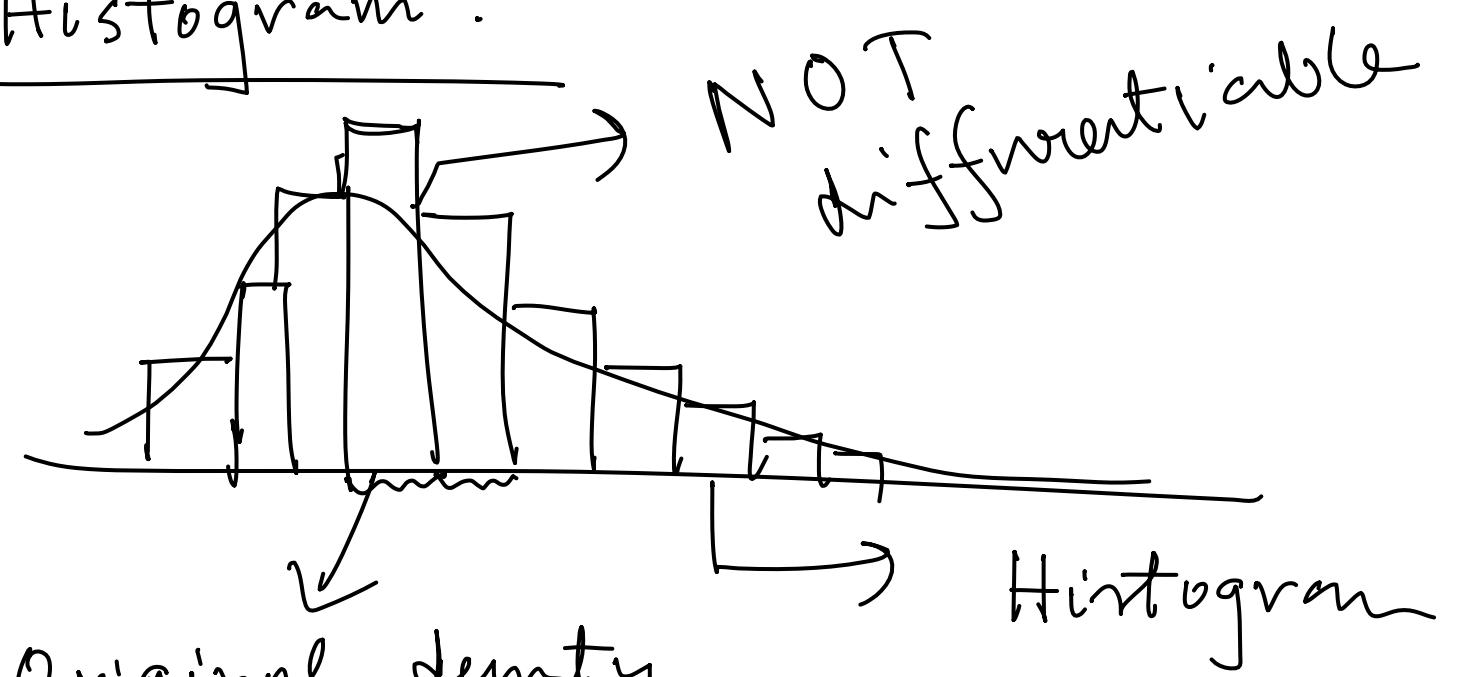
Convex
association



Polynomial
association

ii>

Histogram :-



Original density in a mixture of two densities.
(One is probably from outlier density)

Remark :- Although under some conditions, histogram is asymptotically unbiased estimator of the p.d.f. but it cannot capture the smoothness of the p.d.f.

Quantile - Quantile plot:-

2-sample problem :-

$$X = \{x_1, \dots, x_n\} \sim F$$

$$Y = \{y_1, \dots, y_m\} \sim G.$$

independent data .

Want to test :- $H_0 : F = G$ ag. $H_1 : F \neq G$.

Formulation :-

Step 1 :- Compute $\frac{i}{n}$ -th quantile and $\frac{j}{m}$ -th quantile

from both data set , where $i = 1, \dots, n$ & $j = 1, \dots, m$.

Hence , altogether , we will have $(n+m)$ many quantiles .

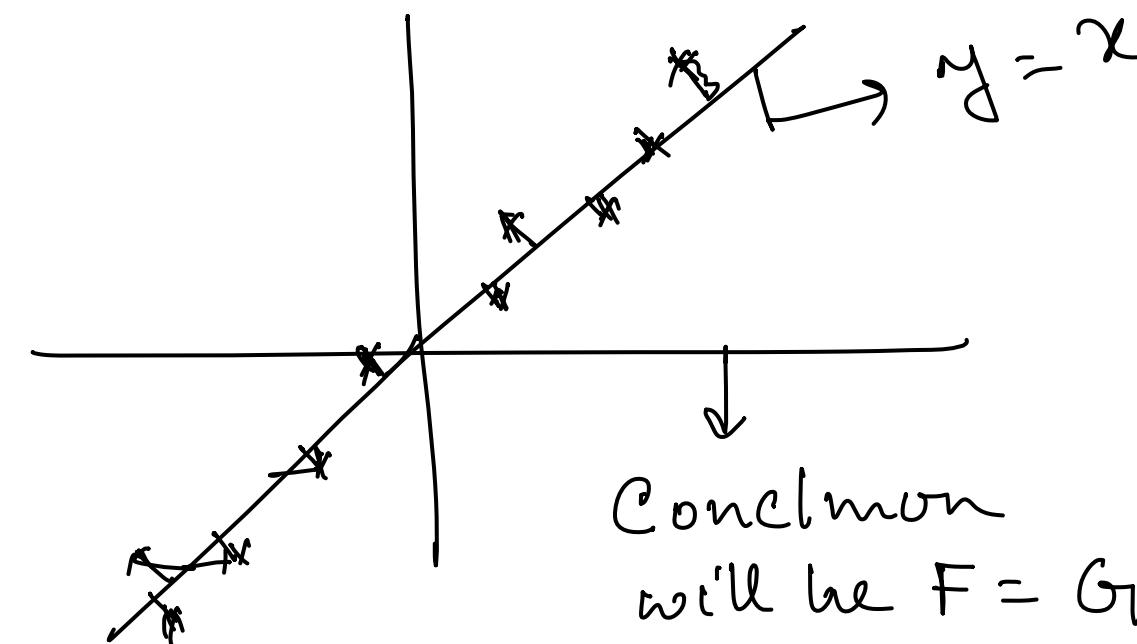
Step 2:-

Plot those $(n+m)$ many quantities.

Implication :-

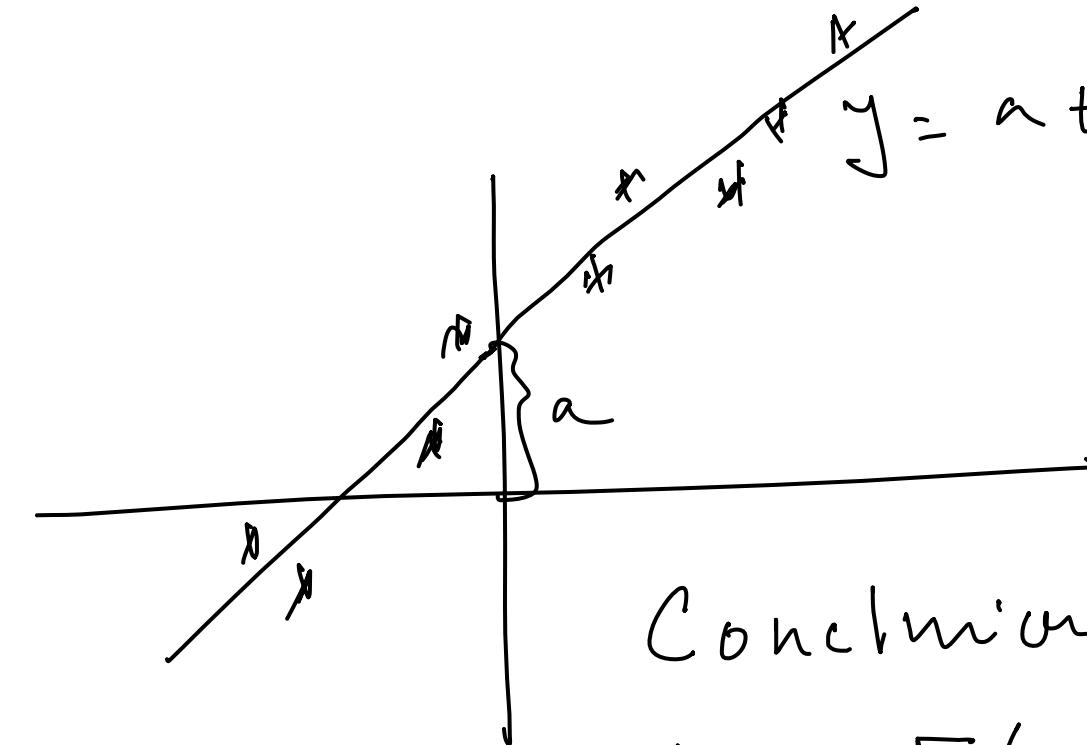
(In the $Q_h - Q_h$ plot).

(i)



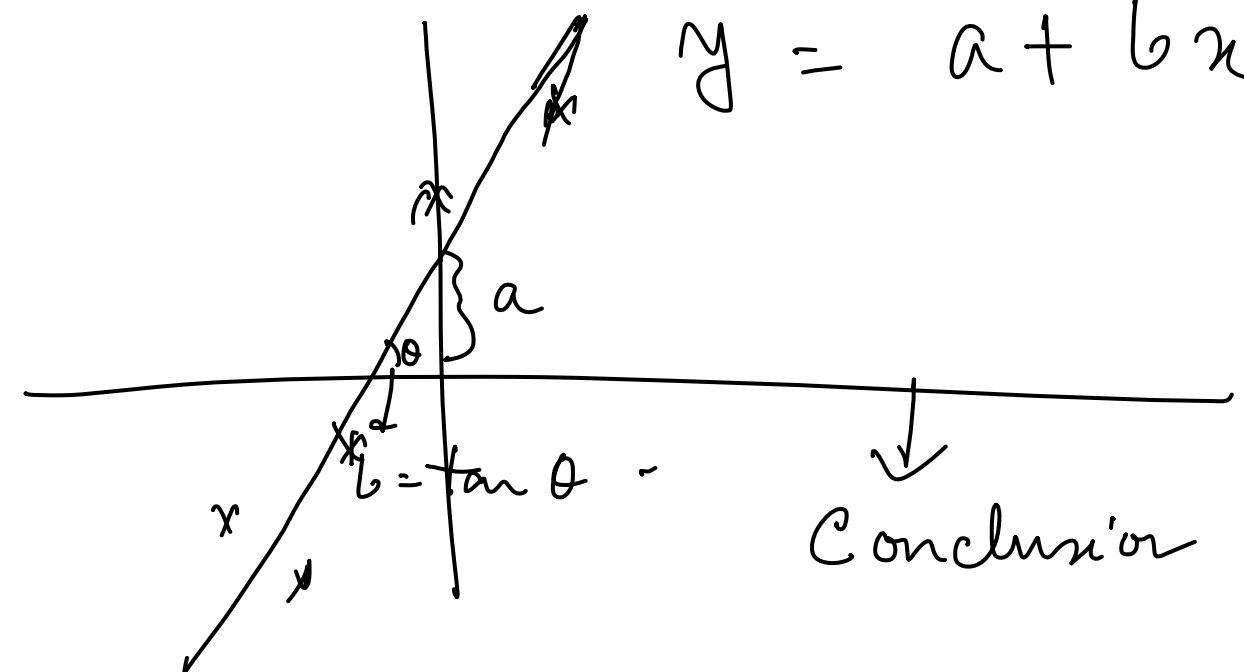
Conclusion
will be $F = G_1$.

(ii)



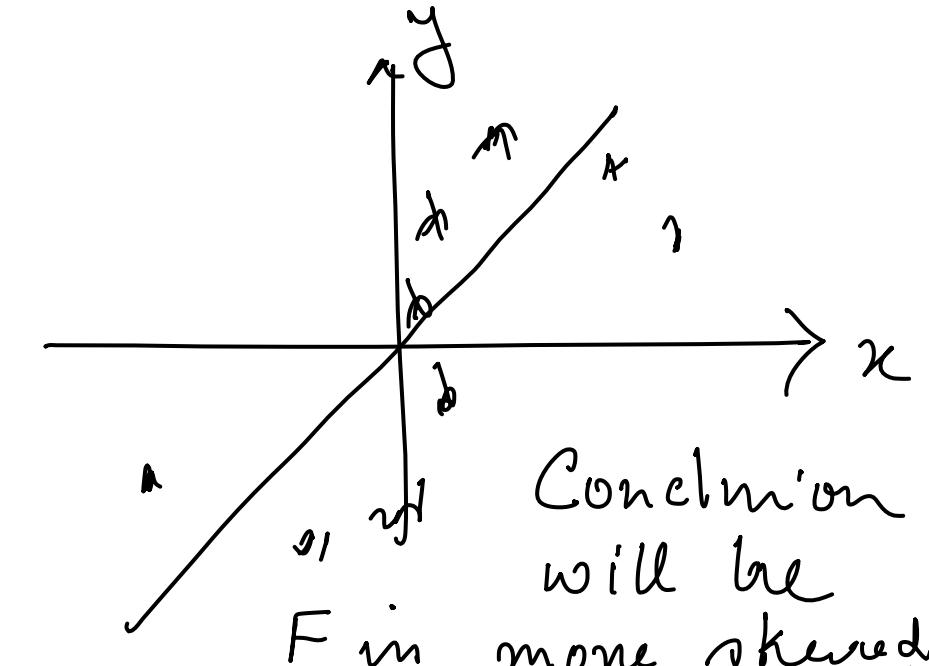
Conclusion will
be $F(x) = G_1(n-a)$

(iii)



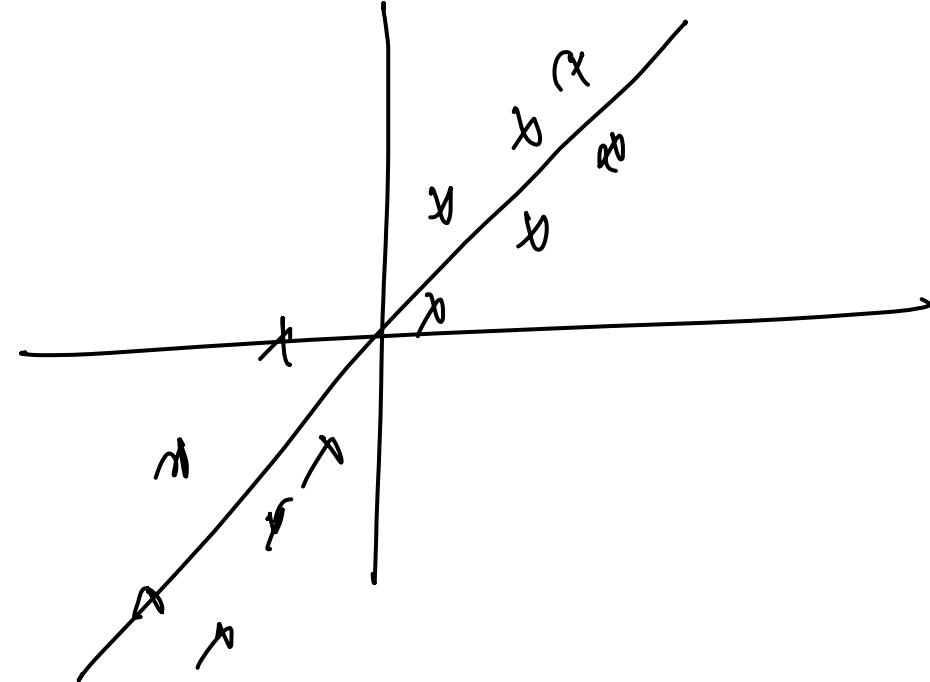
Conclusion will be
 $F(x) = G_1\left(\frac{x-a}{b}\right)$

(iv)



Conclusion
will be
 F is more skewed
than G_1

v>



$$G(x) = (1 - \beta) F(x) + \beta H(x),$$

where β is a small positive number.