## Mutual Information => Filter Based

Mutual Information (MI) is a measure of the dependency between two variable. It quantifies the amount of Information obtained about one random variable through observing the other random variable. It is a fundamental quantities in Information theory.

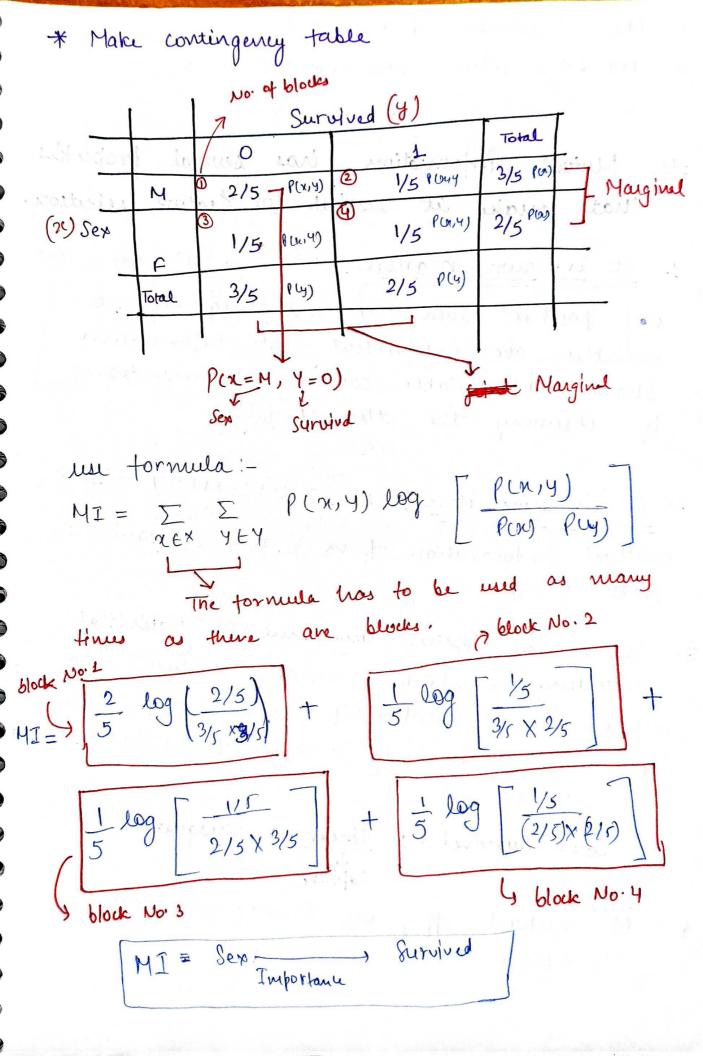
Formula:

$$MI = \sum_{x \in x} \sum_{y \in y} p(x,y) \log \frac{p(x,y)}{p(x)}$$

where

example!-

input	(21) Sex	[Survived](y)	output
	М	0	
	F	1	
	M	0	
	F	0	
	M	1	



\* MI 11 when P(n,y) 11

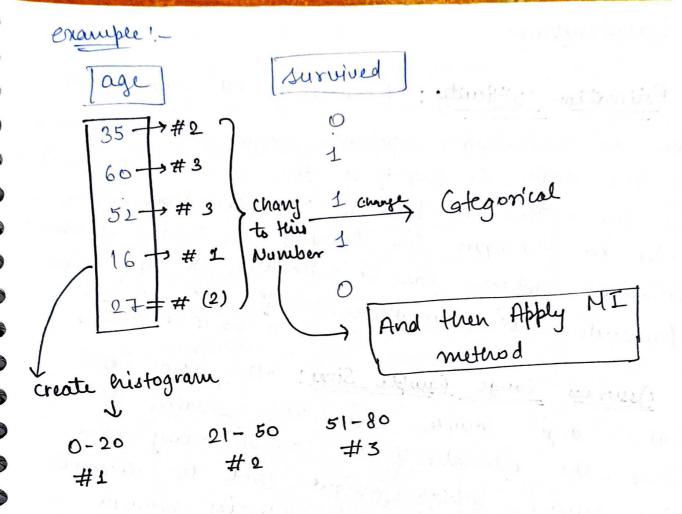
\* MI 11 when P(n) P(y) 11

# Mutual information has several properties that make it useful for feature selection.

- 1. It is mon-negative: MI is always zero always zero indicating that the vaniables are independent. No information about one vaniable can be obtained from by observing the other vaniable.
- 2. It is symmetric: MI(X,Y) = MI(Y, X). The nutual information from X to Y is same as from Y to X.
- 3. It can be capture any kind of statistical dependency: Unlike correlation, which only capture linear relationship, hutual Information lapture any kind of relationship, including Non-linear.

Sex - Survived -> <u>linear</u> -> Chisquare Capture

\* MI nuthod apply on Numerical data but Chi square not.



: Stillage

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## Disadvantage

can be challenging, especially when the aimensionality of the data is highty of the number of samples of low. This is because MI estimation often is low thin igner like binning or density or density relies on federagues like binning or density or density estimation, which can be sensitive to the chosen parameters or assumptions.

- 2. <u>Assumes large fample Sizes</u>: MI works beet with large sample sizes. With smaller sample sizes, the estimates of MI can be noisy and sizes, the estimates of MI can be noisy and less reliable, which night lead to incorrect less reliable, which night lead to incorrect conclusions about the dependenties between
- 2. <u>Computationally intensive</u>: Calculating MI for many features can be computationally expensive, especially for continous variables. This neight especially for continous variables on for application be problematic for large datasets on for application where computational resources or time gree limited.

4. Toifficulty with Continous Variable: While MI

theoretically applies to Continous Variables, in practice of the Office difficult to estimate MI between continous Variables due to the need for accurate density estimate MI between continous variables

due to the need for accurate dousty estimate, notice in a concludingly problem in its own if binning

5. <u>No Birect ardication of the Nature of Relationships:</u>

Although MI can identify the existence of a relationship between variables, it does not provide direct information about the nature of this relationship. (eg. linear, quadratic, etc.) This contrast with methods such as correlation, which with methods such as correlation, which directly indicates the strength and direction of a linear relationship. MIT > relation of but not provide nature linear, quadratic

6. Doesn't Account for Redundancy: Mutual information measure the relevance of individual features to the target variables, bout it doesn't take the features among features into account the redundancy among features wiright individually have highly correlated, they target, but if they are highly correlated, they target, but if they are highly correlated, they might not provide much rinique information.

This can be lead to the section of redundant to the section of redundant.

what if strong relationship between 41 42 multicollinearity.