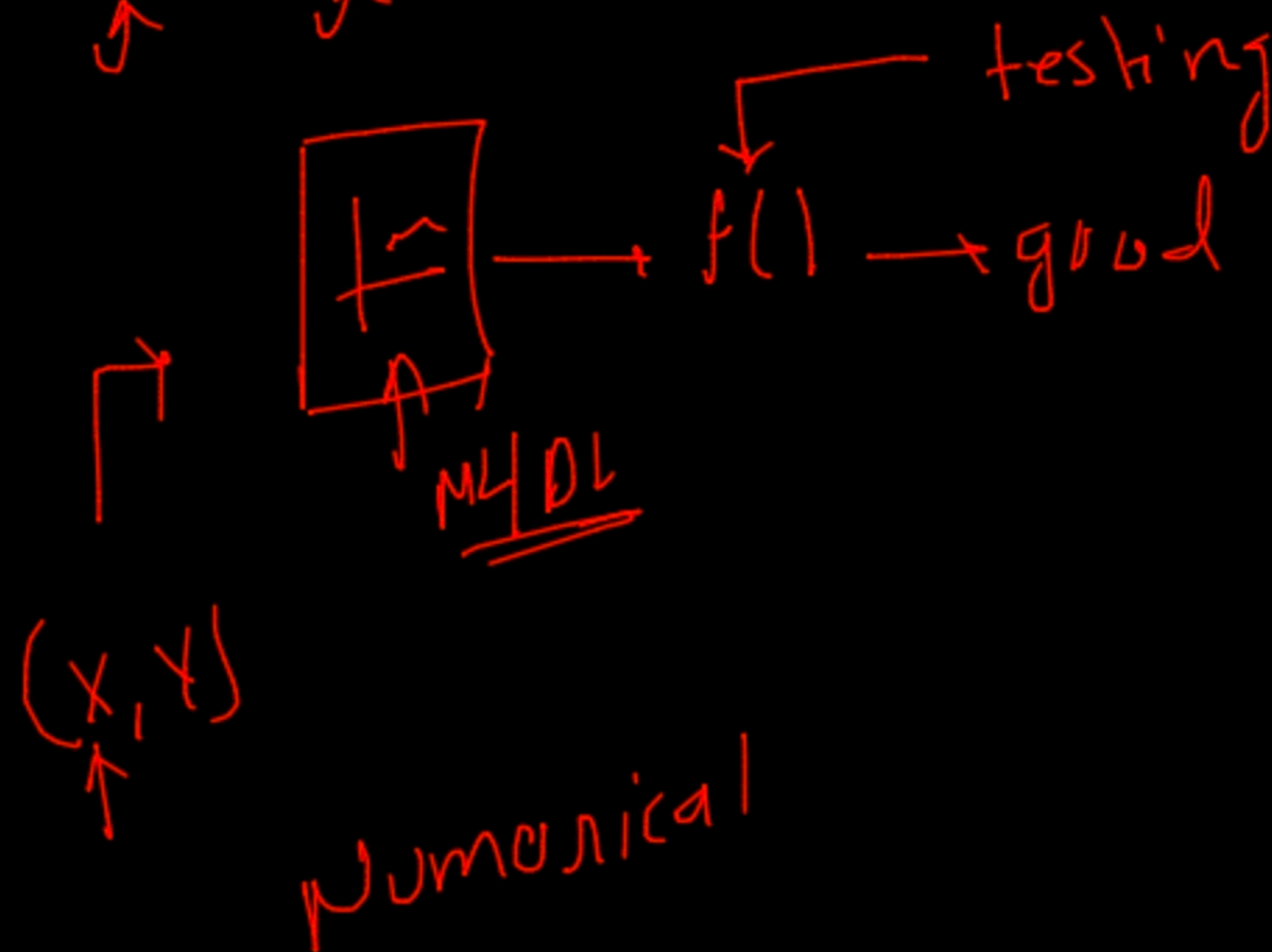


$P_x \rightarrow \text{Numerical}$

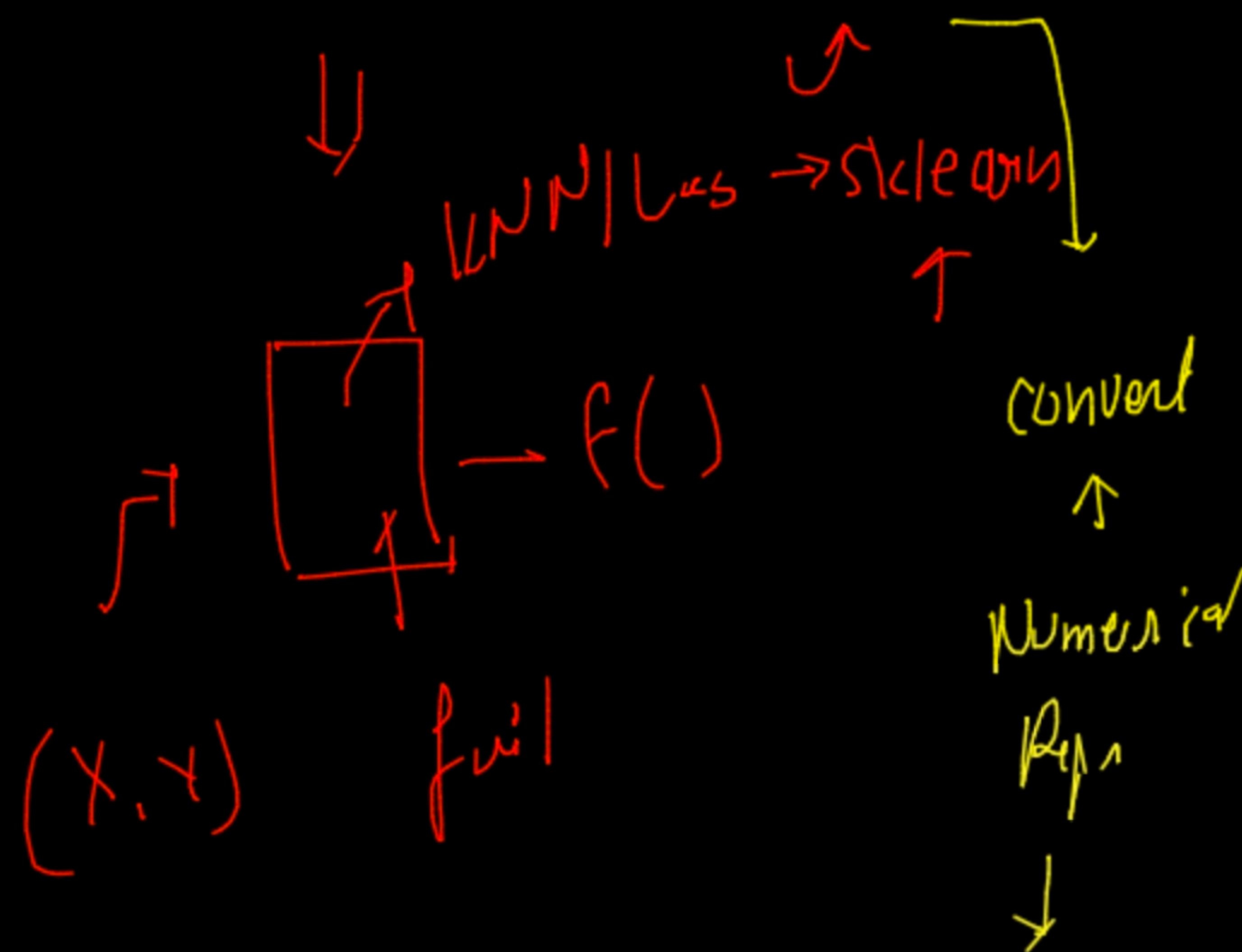
eg:

	X				Y
	cid	income	cs	# of loans	Status
1	14	750	1		Y
2	15	650	2		Y
3	16	350	0		N



BUT

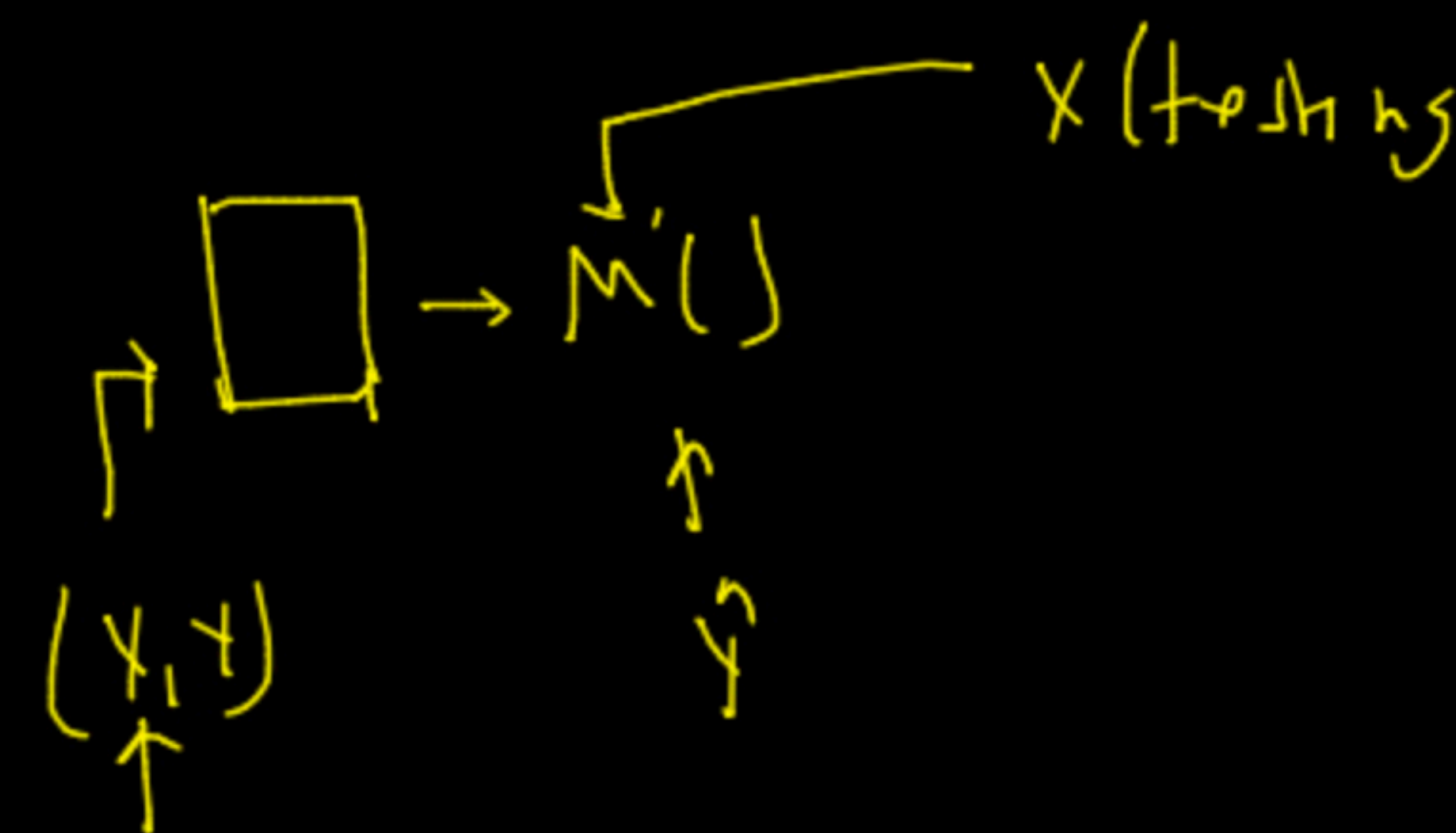
	X					Y
	cid	income	cs	# of loans	city	Status
1	14	750	1		Tirunelveli	Y
2	15	650	2		Tirunelveli	Y
3	16	350	0		Tirunelveli	N



$f() \leftarrow m()$

eg. $\overbrace{\text{weight hair-color country}}^x \text{ --- } \overbrace{y}^y$

→ 64 Black MS 180

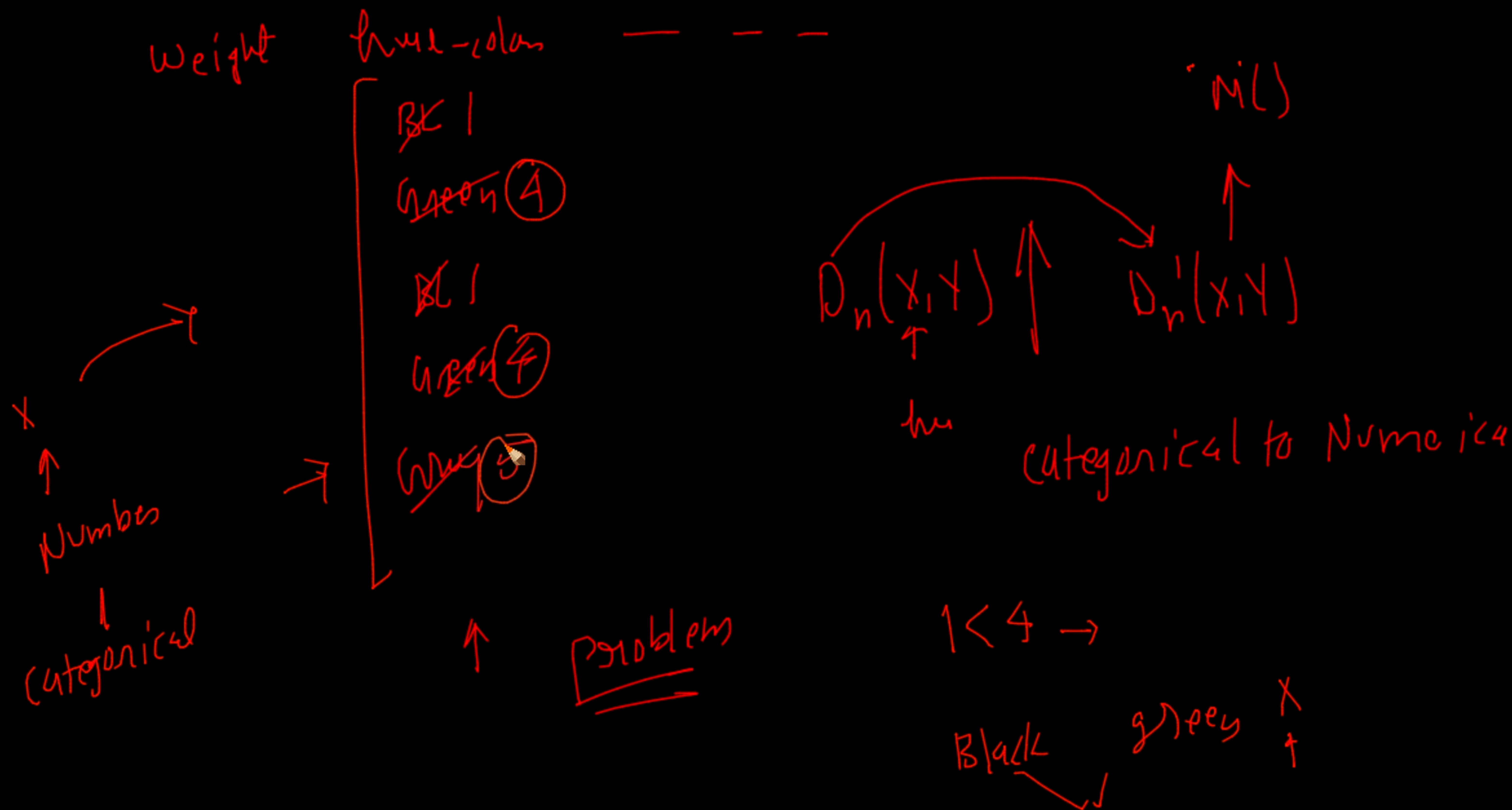


categorical → number

Int - hair-color → { BL, Brn, Red, Green, Grey } at
 ↑ ↑ ↑ ↑ ↑
 '1' '2' '3' '4' '5'

$P_n(x, y)$ hair-color

at the end



$D_n \rightarrow$ 'Rating'
good
v good
good
Bad
Bad
good

transfor
→

Rating
2
1
0
0
1
→ ML
↑
OK
4

↑
categorical

Bad $\rightarrow 0$
good $\rightarrow 1$
v-good $\rightarrow 2$

ONE HOT ENCODING



simple →

hair-colors



5 unique → {BL, BR, Red, Green, Gray}

↑

5

(6D)

2D → 6D ↑

$f'()$



$M(X,Y)$

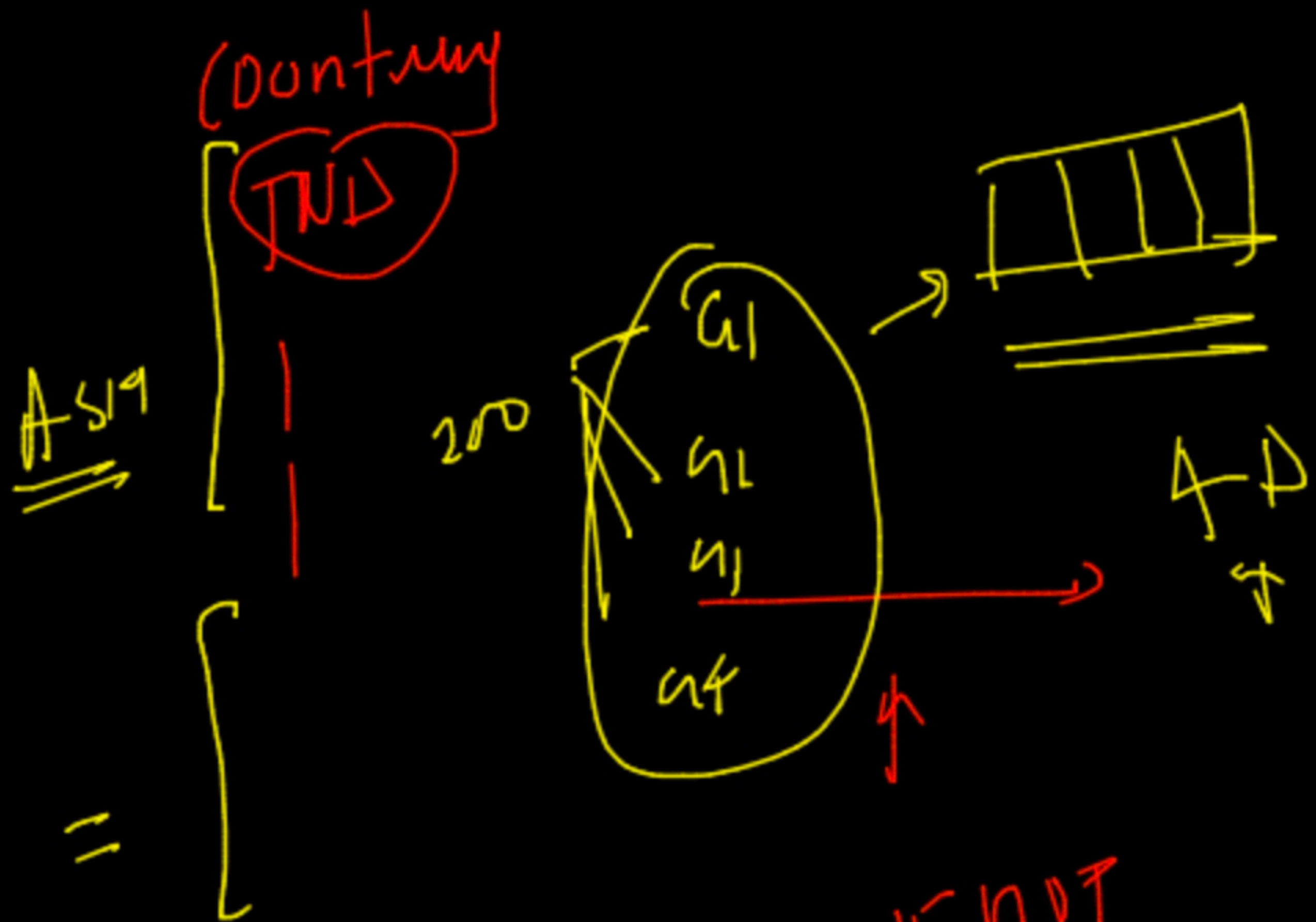
P_h

weight	hair-colors	BL	BR	Red	Green	Gray
54	Black	1	0	0	0	0
56	Black	1	0	0	0	0
51	Green	0	0	0	1	0



4

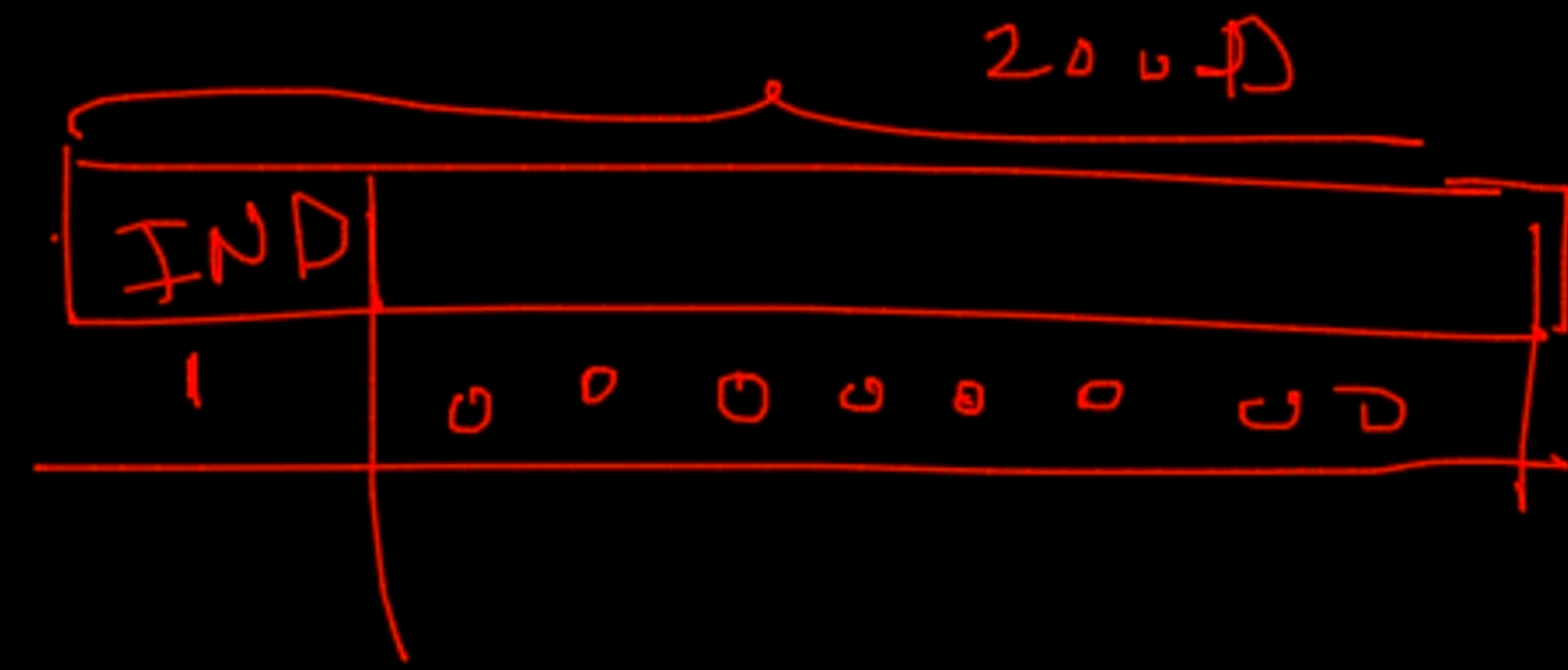




200
↑
category

ONE HOT
encoding

sklearn
pd.get_dummies



good → col → 20 unique → domains
↑
↑
categorical Dimensions

Missing value imputation

$D_n \rightarrow$

	income	cs
	3500	350
	17	410
na	19	780
	14	19
	9	350

x	fail
status	
yes	↑
yes	↑
yes	↑
yes	↑
yes	↑
no	(x, y)

$$350 + 400 + 780 + 36 / \rightarrow \underline{354}$$

$$\frac{35 + 17 + 14 + 9}{4} = 21$$

- mean
- median
- mode

i) take all non-empty val^u
 (ii) compute mean/median/mode
 and put in place of missing
 val^u

Bias-Variance Tradeoff

$$K=1$$

$$K=1$$

underfitting

$P_n \rightarrow 100\%$

now we can
understand mathematically
 \Rightarrow Bias-Variance Tradeoff

$$P_x \rightarrow \boxed{2} \rightarrow F'() - ?$$

ML/DL
 \uparrow

$$\text{generalisation error} = \text{Bias}^2 + \text{irreducible error} + \text{variance}$$

\downarrow
 $\{ \text{future unseen data} \}$

Log Bayes \rightarrow assumption high bias

$$P_x \rightarrow \boxed{LR()} \rightarrow \text{xy2d13}$$

$$\boxed{LR}$$

