

$$\begin{aligned}
& P[Y \neq g_m^{NN}(x) / X=x, X'=x'] \\
&= P[\underbrace{Y=0}_{\downarrow}, \underbrace{Y'=1}_{\nearrow} / \underline{X=x}, \underline{X'=x'}] + P[Y=1, Y'=0 / X=x, X'=x'] \\
&= P[Y=0 / X=x] P[\underline{Y'=1 / X=x, X'=x'}] + \quad \downarrow \\
&= (1-\eta(x)) (\eta(x')) + \eta(x)(1-\eta(x')) \\
&\xrightarrow{m \rightarrow \infty} \underline{2\eta(x)(1-\eta(x'))}
\end{aligned}$$

$X' \rightarrow X$ as $m \rightarrow \infty$
 $\eta(x') \rightarrow \eta(x)$ as $m \rightarrow \infty$

$$R^{NN}(n) = 2n(n)(1-n(n))$$

$$E[R^{NN}(x)] = 2E[n(x)(1-n(x))] = 2E[\eta(x)(1-\eta(x))]$$

R^{NN}

Also, $R^* = E[\eta(x)]$,
 where $\eta(x) \equiv \min(n(x), 1-n(x))$

By adding and
 subtracting
 $2(E[\eta(x)])^2$

$$\begin{aligned} &= 2E[\eta(x)](1-E[\eta(x)]) - 2\text{var}(\eta(x)) \\ &\leq 2R^*(1-R^*) \leq 2R^* \end{aligned}$$

In the lecture, I just assumed $\eta(x) = n(x)$.
 The above is the generic derivation.

LECTURE-5

k is odd

$$R^{kNN}(x) = n(n) + (1 - n(n))$$

\downarrow

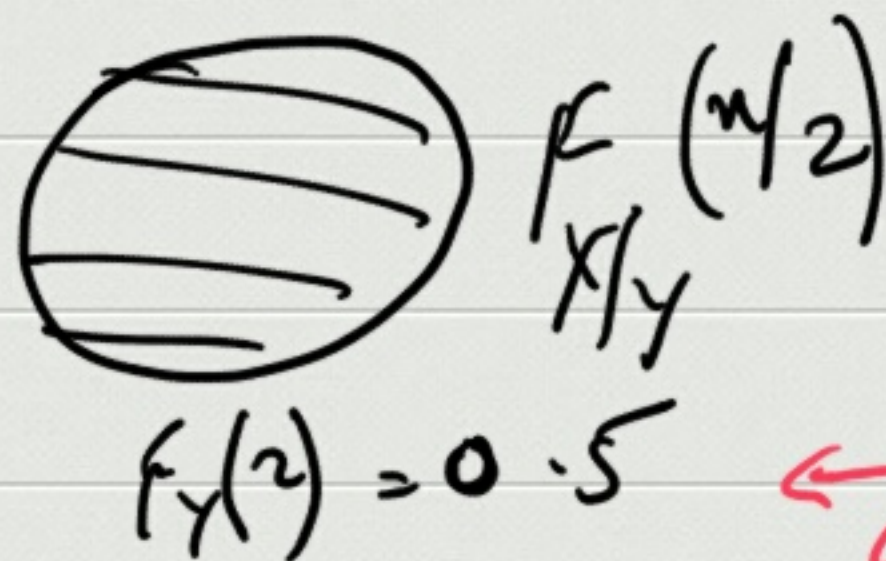
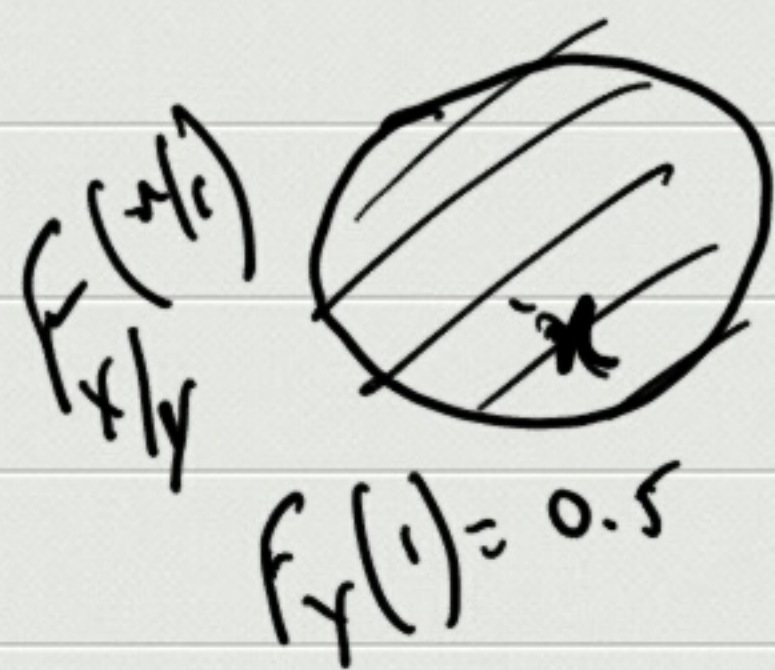
$$\sum_{j=0}^{\lfloor \frac{k}{2} \rfloor} \binom{k}{j} (n(n))^j (1 - n(n))^{k-j}$$

$$\sum_{j=0}^{\lfloor \frac{k}{2} \rfloor} \binom{k}{j} (n(n))^{k-j} (1 - n(n))^j$$

$$R^{kNN}(n) = \eta(n) P\left[\sum_{i=1}^k z_i < 0\right] + (1 - \eta(n)) P\left[\sum_{i=1}^k z_i > 0\right]$$

$$= \eta(n) + \underbrace{(1 - 2\eta(n))}_{> 0} \underbrace{P\left[\sum_{i=1}^k z_i > 0\right]}_{\text{circled}}$$

$$\eta(n) < 1/2$$



$k \uparrow$, then

$$\therefore R^{(2k+1)N/N} \leq R^{(2k-1)N/N} \quad \forall k \in \mathbb{N}$$

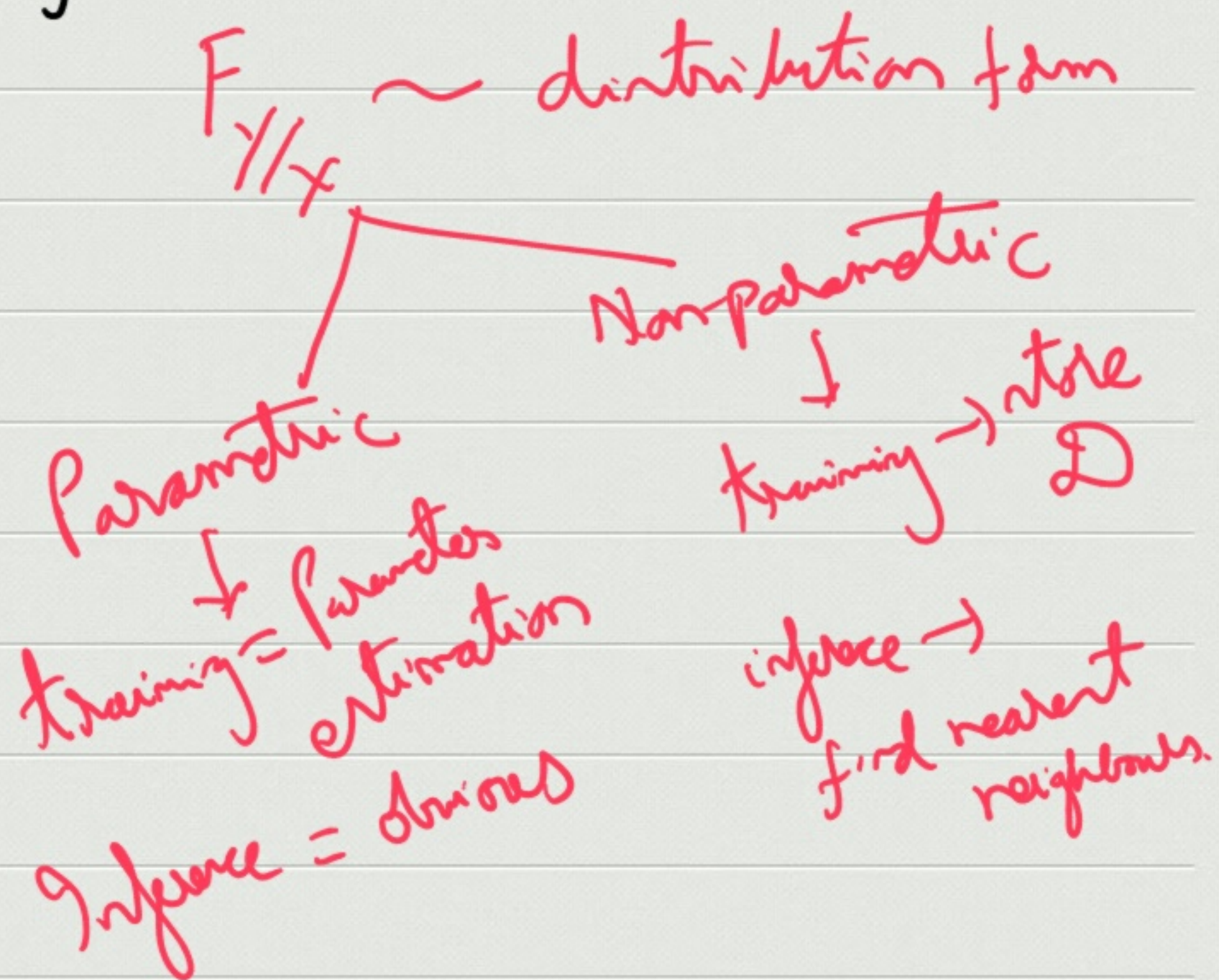
Counter example with finite 'm'!

Non-deterministic Models

kNN \longrightarrow Estimate distributions from samples of the \mathcal{I}

Deterministic Models

Cy: linear model
quadratic model.



EXAMPLE OF ANOTHER MODEL

$$f(x) = \sum_{i=1}^m \alpha_i y_i \underbrace{k(x_i, x)}$$

↓
kernel of x_i to x

Model = $\{f, y\}$

training \rightarrow obtaining α .

Inference \rightarrow evaluate $f(x)$.

Deterministic modeling.
Parametric.