Gravssian discriminal analysis Naive Bayes



Generative Leaning algorithms

=> So fan we've mainly been talking obout leaning algorithms that models

P(4/x;0)

La Such algorithmes are colled disconnentise leaning algorithm.

Here we'll talk about algorithms that
instead togg to model P(X14) (and P(y))

These algorithms are called

generative rearring algorithms.

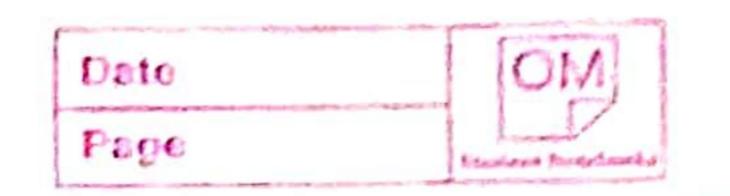
After modeling P(y) (colled the class positions)
and P(x/y), our algorithm can then use
Bayes onle to derive the posterior
distribution on y given a

P(y121) - P(2(16)P(6))

> P(x15) P(5)

angmax P(y|x) = angmax P(x|y)P(y)

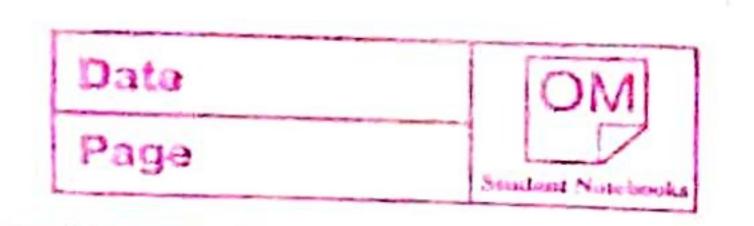
= angmax P(x 14) P(4)



* Gaussia discriminat andysis (GDA)

$$\phi = \frac{1}{m} \sum_{i=1}^{m} 1 \{y^{(i)} = 1\}$$

$$\frac{1}{2} = \frac{1}{2} \left\{ \frac{1}{2} \left(\frac{1}{2} \right) \right\} = 0$$



$$M_{\bullet} = \sum_{i=1}^{\infty} 4\{g^{(i)} = 1\} \chi^{(i)}$$

$$\sum_{i=1}^{m} 1 \left(y(i) \right) = 1 \left(x(i) \right)$$

$$= \frac{1}{m} \sum_{i=1}^{m} \left(x^{(i)} - \mathcal{M}_{\delta}(i) \right) \left(x^{(i)} - \mathcal{M}_{\delta}(i) \right)^{T}$$

- Flyld) is multivariete gaussian than
 P(yld) necessarly follows a logistic
 function.
- The Converse, however is not true; i.e.
 P(yold) being a logistic function does not
 imply P(Xly) is multivaride gaussian.
- This shows that GDA makes stronger modeling assumptions about the data than does logistic oregression.
- Them modeling assumptions are connect, then aDA will find better fits to the data, and is a better model.
- In Contrast, by making Significantly weeken assumptions, logistic oregression is more orobust and less sen sittle to incorrect modeling assumptions.