CATEGORISATION OF LEARNING

1. Based on o/p type - regression v/s classificat^n
2. Learning strategy - supervised, unsupervised, semi-supervised, reinforcement learning
3. Lazy v/s eager
4. Parametric v/s Non-parametric
5. Discriminative v/s Generative

* BASED ON OUTPUT TYPE

REGRESSION	CLASSIFICATION
PREDICTED VARIABLE IS CONTINUOUS	PREDICTED VARIABLE IS DISCRETE (1 of K classes)
eg. Predict house price	eg. predict whether cat or dog

	LAZY	EAGER
EXAMPLE	KNN	DT, LINEAR REGRESSION
TRAIN TIME	0	$\neq 0$
TEST TIME	USUALLY LONGER	USUALLY QUICKER eg. for Linear Regression $\hat{y} = X\hat{\theta}$
MEMORY	STORE /MEMORISE ALL DATA	PARAMETERS ONLY
UTILITY	USEFUL FOR ONLINE SETTING	

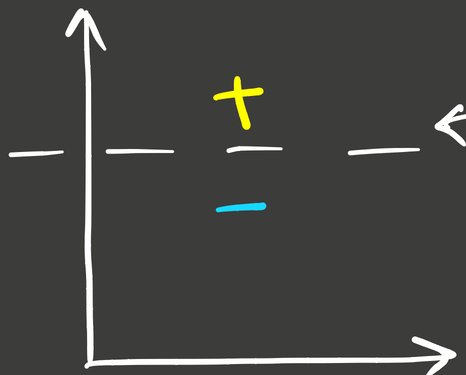
PARAMETRIC V/S NON- PARAMETRIC

	PARAMETRIC	NON- PARAMETRIC
EXAMPLES	LINEAR RGGRESSION	KNN, DT
PARAMETERS	# parameters is fixed w.r.t. dataset size.	# parameters grows w.r.t. dataset size
SPEED	USUALLY QUICKER	USUALLY SLOWER
ASSUMPTIONS	STRONG ASSUMPTIONS (like linearity in LINEAR REGRESSION)	NO OR FEW ASSUMPTIONS

Question:

KNN is non-parametric and linear model parametric?

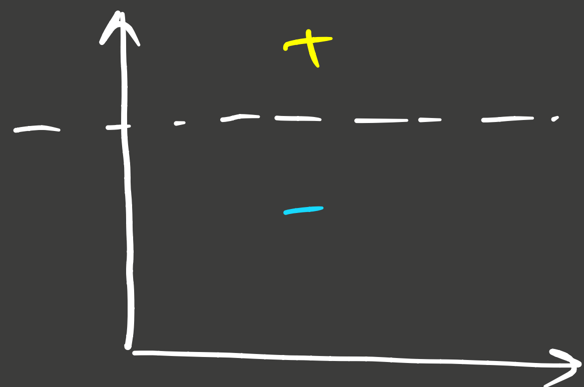
Consider data like:



← classification

Decision boundary (Linear model)

params = 2 ($y = mx + c$)



params = 2

Decision boundary for KNN is linear

Add data points

params = 2

Linear model decision func^n still linear

params >> 2

Decision func^n for KNN has high degree

SUPERVISED	UNSUPERVISED	SEMI-SUPERVISED	REINFORCEMENT
I/P FEATURES + O/P LABELS IN TRAIN SET	NO OUTPUT LABELS	OUTPUT LABELS FOR SUBSET OF DATASET	GOAL, ACTION, REWARD, ENVIRONMENT, STATES
eg. Linear Regression, SVM, ...	eg. KMeans clustering, Autoencoders...		eg. Q-learning.

DISCRIMINATIVE V/S GENERATIVE

	DISCRIMINATIVE	GENERATIVE
Example	Logistic Regression, SVM	Naive Bayes
Data generation	Can<u>not</u> generate new data	Can generate new data
Question	what side of decision boundary is instance on? ↓ Models decision boundary	what's likelihood this class generated this instance ↓ Models distribution of classes
Goal	Estimate P(Class | I/p Features)	Estimate P(I/p Features | Class) & P(Class) to get P(Class | I/p Features)

ASSUME I/P FEATURES 'x', O/P = Elephant (y = 1) and dog (y = 0)

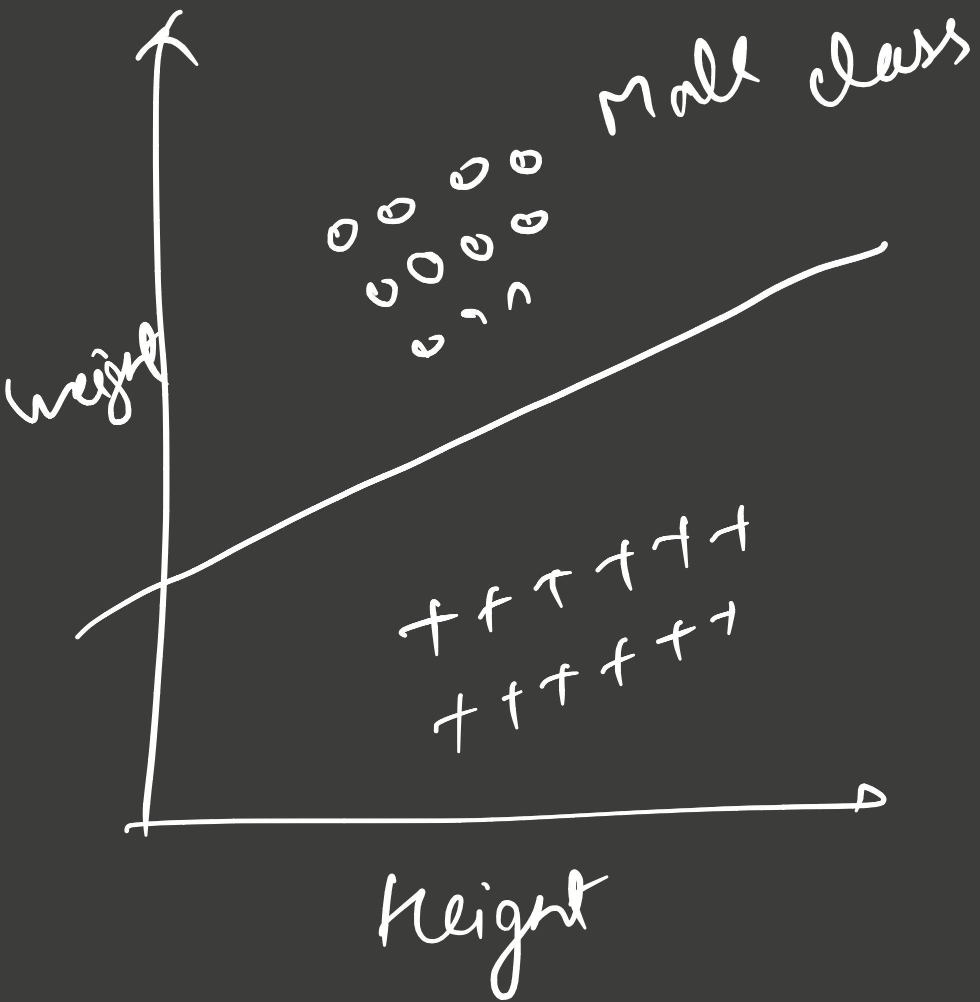
DISCRIMINATIVE

1. learn a decision boundary b/w dogs & elephants
2. For new instance, see which side of decision function the instance belongs to

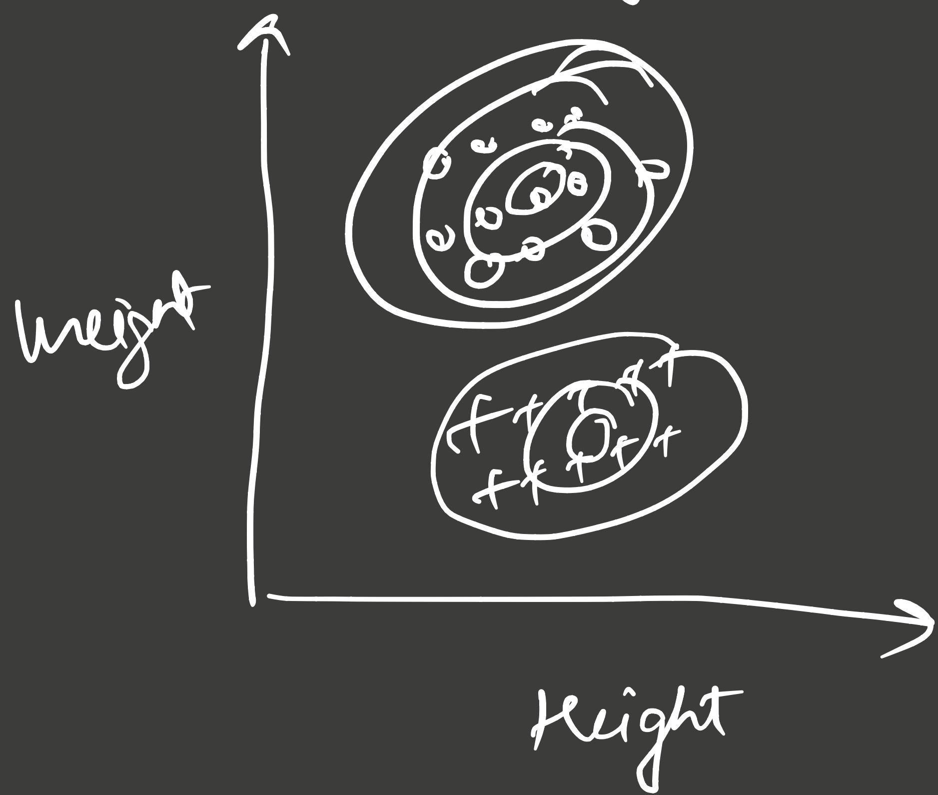
GENERATIVE

1. Look at elephants & build a model of elephants
2. Do same with dogs
3. For new instance, match against both dog & elephant model to see which one is closer

Discriminative



Generative algorithms



$$\frac{P(\text{male} \mid h, w)}{P(\text{Femal} \mid h, w)}$$