My the sic testing is an exential procedure statistics. A hypothesis test evaluates two mutually exclusive statements about a folulation to determine which statement is best sufficient by the sample date when we say that a finding is statistically significant, with help of hypothesis test. · Null 4y70 thesis -> It is a general stelement or default position that there is no gelation shift between two measured the noment or association among growths

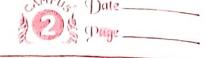
Alternative Hypothesis > It is used in testing that hypothesis. It is usually taken to be that the observations are the nesult of a neal effect. I Penformance Analysis & In machine learning it is very exential fast of any · Classification Accuracy & It is what we usually mean It is natio of no of connect fredictions to the total no. of input earlies. o Confusion Matrix > It gives us a matrix as
outfut and describes complete

ferformace of model let assume | Bresid | Bredict On testing own model on 165 samples we got the following tes.

(p (Boolsteafing & It is a method of sample newse The idea is to use the
1	Bool straying of the stea is to use the
	to estimate the legislation
	distribution Then samples can be drawn from the
	distribution then samples the compline distribution
	extinated population and the earnfling distribution
	of any type of estimator can itself be
	estimated.
	" A like alian
	There eve there tyles of bookstrajings
0)	Nonfarametric & A sample of same size of the
	duta is tured in the sales
	with reflecement what does this mean It means
	That if you measure to samples, you create a
	new earlie of eize 10 by gellicating come
	of the sample that you have already seen and
	omitting others
00)	Semi Presameteric & It can only refereduce the items
	Somi Parametoric & It can only referoduce the items that were in veriginal sample.
	It assume that the fogulation includes other
	Heme that are similar to observed sample by
	sleme that are similar to observed sample by sampling from smoothed version of the sample
	hickogeram.
00.	Parametric & It axumes that data comes from
	a known distribution with unknown
	Parameters you estimate the parameters from
	the data that you have and then you use
	the estimated distributions to simulate the
	samples,
	All above camples methods are cimulation based
	ideas.
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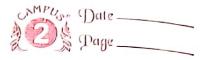
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	Page Page
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/	has the Ot Mediction as
	direct estimate The besic idea is to split
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	the terain the subsets - one
	the toraining data into two subsets - one is used to train the grediction rule and
	then the other subset is used to excess
	The acoustic
	There is a small peoplem with this
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	Ignalication engage is lard and estimated
	Exediction errors is based on freelictor developed
	on smaller semple N > N-N K. So Crow-velidation
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	frediction eroson than you think However with
	10-10ces crass validation (ant he I
	our secause you are using at last con
	of your lample



Since Bayes theorem feworides a feincilla way calculate the fasterion feobability of each hypothesis given the training class, we can use it as the basis from a straightformed learning algorithm that calculates the peobabilities for each fourible hypothesis, then outfuts the most feobable. This earlier considers such a bornet force bayesian concept learning algorithm then comforces it to concept learning algorithm the way shall see, one interesting result of his comforces on in that under certain conditions semi algorithms outfut the same hypothesis as this brank force Rayadian. • learned force Rayadian • learned france Rayadian • learned france Rayadian • learned from the forterior probability P(h D) of his given D • P(h D) = P(A) P(B) P(B) P(B) • Rayes Theorem > The forterior probability P(h D) of his given D • P(h D) = P(B) = Z P(B Di) P(Di) • Theorem of Total Brobability > If events A. A. are mutually estimated and their conditional defendencies using a disable and their conditional defendencies using a disable distribution and also use ferobability theory for probability because these networks are published distribution and also use ferobability theory for		
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Perediction and anomaly detection		distribution and also use perobability theory for
IA		prediction and anomaly detection
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3) i) Lamanckian Evolution & He fro fored that
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3) Baldwin Effect & If a species is evolving in
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