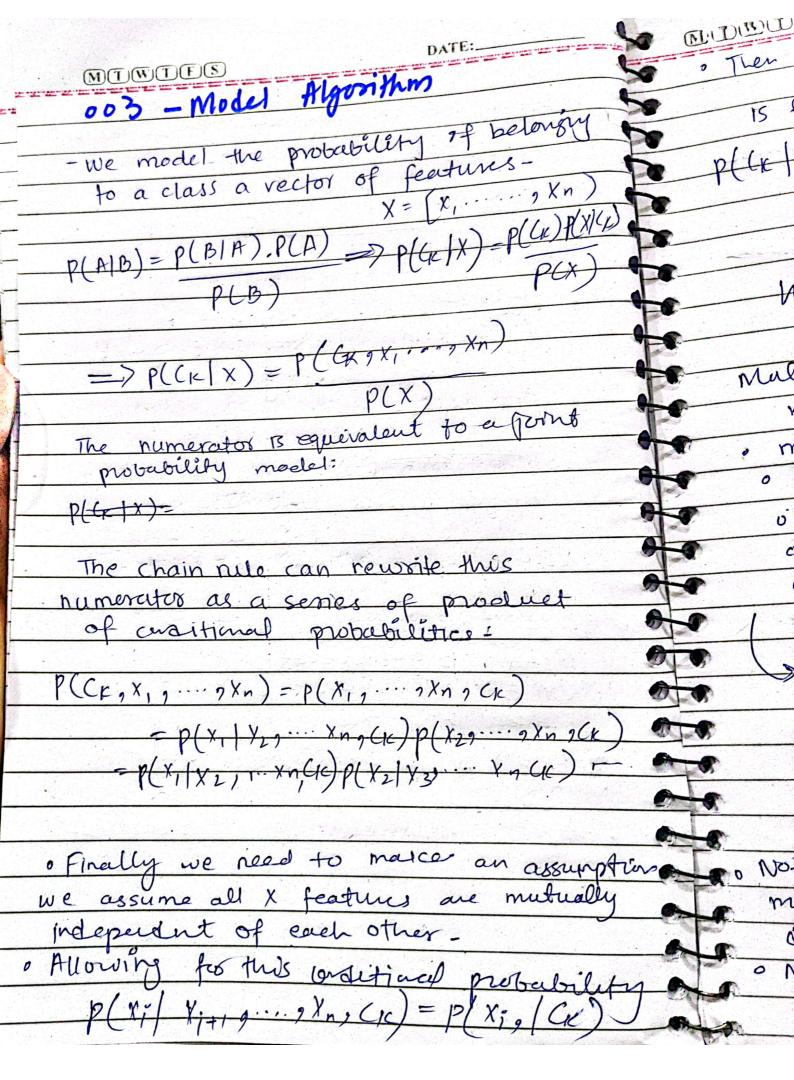
Naigres bayes section	1
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· In this section we will begin a dissussion	4
on using raw string text for machine leaver o	9
	-
The general idea is general is known as	-
"Natural Language processing"	9
Section Overview	
· Naive Bayes Algoritm and NLP	_
· Extracting features from text Data	
· Text Classification project	
- beep in mind:	
This section focus on supervised	
Learning text tasks. We will discuss	
unsupervised fext task later on.	
2 - Naire Bayes Algorith	
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· Bayes Messon	
o Naive Bayees is the shorthand for a	
Set of algorithm that use Bayes Theorn	
for superised learning classification.	
· Bayes Therom is a probability formula	
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affer his death I Richard price edited and published his notes.
lo Bayes theorn
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· P(A1B) B probability of event A gue
feet B is true
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probability of 11 desires
· ρ(β) probability of A occurry. • ρ(β) B probability of B occurry



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9	Multiple Variations of Naive Bayes
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9	o Complement Naive Bayes
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9	o Categorical Nouve Bayes
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0	Multinemial Naige Bayes).
	we will focus
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9 0	Note how a higher alpha values will be
9_	mere smoothing , giving each word les
9	o Now lets more on to focusing on feature
9	expect on general
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4 the Feature Extractor
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- Main Method of feature Expactu
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OTF-IDF
Term Frequency Inverse Document Frequency
· Count vectorization peats every works
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The feature/word.
For larger documents 3 matrice are
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will be zero.
- stopwards - a, the
TF-10F - will court and inverse
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#7 bding
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"This is another line".
11 Corpa J
for Skleur feature expaction text
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