COMP3608 Naïve Bayes

## **Email Classification**

#### Aim

The aim of this study is to implement text classification of emails using the Naïve Bayes classifier for spam detection.

Spam emails are usually sent to derive cash from the user either directly by tricking the user into purchasing something or indirectly by ticking them into parting with information. The classification of emails aims foremost to protect the unaware user from the malicious intent of spam emails. Classification of emails also saves the user the time and hassle of manually classifying and deleting spam.

### Data Preprocessing and Feature Selection

The files in the sample set *Lingpspam-mini600* are represented as a "bag-of-words", where words are extracted from the file and treated as a feature. The *document frequency* feature selection method was used, to select the 200 words which occured in the most documents as features, and used to build a classifier for the given documents. The features are then weighted using *td-idf* and normalised using *cosine normalisation*.

- 1. For each file in the sample set *Lingpspam-mini600*:
  - 1.1. Open the file and read it line by line.
  - 1.2. Replace all punctuation and special symbols from each line with a space. (e.g. "don't" becomes "don", "t")
  - 1.3. The sub-corpus the line belongs to is determined by checking if the line begins with "Subject:". If it does the words within the line will be added to the subject corpus, otherwise they will be added to the body corpus.
  - 1.4. Words from each line are extracted using space as a delimiter.
  - 1.5. Stop words, numbers and words containing digits are removed.
  - 1.6. A counter is created for both corpora. For each word that appears in the email add it to its respective counter.
  - 1.7. For each word that appeared in the counter for an email, it is added once to the counter for the corresponding subcorpus.
- 2. In each corpus the words with the top 200 Document Frequency (words which are appeared in the most number of documents) were selected as features for that corpus.
- 3. For each feature, its *tf-idf* score is calculated.
- 4. The *tf-idf* values are normalised using *cosine normalisation*.

The removal of stop words in text processing filters out common words that offer little value for classification. Before stop words were removed, there were 19886 and 1074 unique words in the body and subject corpuses respectively. After their removal, there were 19386 unique words remaining in the body corpus, and 915 words in the subject corpus.

COMP3608 Naïve Bayes

l 15 /	LDI		1 -	D.D.	II <b></b>	1	DE		l <b>5</b>	1	DD I	l - D		LDD
Feature	D1		re 1	DF_	Featur		DF	4	Feati		DF		ture	DF
sum	30	*		7	spanis	h	5		secre		4		these	3
summary	26	v		7	list		5		addr		4		fer	3
english	24	III .		7	time		5		fwo		4		ne	3
language	21	II .		7	word		5		rea		4		me	3
free	20	1 0		7	softwa		5		reque		4	1	ite	3
disc	19	III .	SS	6	languag	-	5		informa		4		eck	3
1 .	query   18   slip			6	linguis	st	5		systems		4	reference		3
	linguistics   15   conference			6	jobs	_	5		american		4		ground	3
comparative	comparative   13   lang			6	research		5		intuitions		4	cd		3
sex 13		*		6	native	е	5		great		4	teaching		3
words	12	11 0	german		resourc	es	5		doub		3	decimal		3
opposites   12		- 11	money		www		4		change		3	latin		3
book	10	II	op	6	unlimit	$_{\rm ed}$	4		synth		3		mes	3
email	10	, II		6	prograi	$^{\mathrm{ns}}$	4		cred		3	1	$_{ m nting}$	3
method	9	11 *		6	web		4		reques		3		pa	3
job	9	III .		6	bannin		4		futu		3	1	rpus	3
call	9	III .		6	phoneti	ics	4		tonig	,	3	1	plete	3
japanese	8	II.		6	summe	-	4		mal		3		orld	3
correction	8	11 0		5	books	3	4		compa		3		lution	3
announcemen	nt 7	neede		5	pig		4		hey		3	dia	lect	3
Feature	DF	Feature	DF		Feature	DI			eature	DF		ture	DF	
information	205	fax	116	in	terested	86		S	pecial	78	S	ite	69	
language	192	order	108		year	86	- 11		line	78		$\operatorname{ext}$	68	
mail	183	call	103		day	86	- 11		days	77	1	ead	68	
university	179	form	101	11	vorking	85	- 11	ir	nternet	76	po	$_{ m oint}$	68	
time	178	research	100	i	$\operatorname{nclude}$	85	11		back	76	W	$\operatorname{eek}$	67	
list	171	linguistic	99		case	85			nerican	75	1	go	67	
address	165	state	99		based	84	- 11	S	ervice	75	1	ook	67	
english	159	subject	98		ve	84		S	ystem	74	de	ear	66	
linguistics	156	years	98		note	83	- 11	bı	usiness	74		ost	66	
http	156	world	98		home	83	- 11		full	74	ma	king	66	
people	146	contact	97		$_{\mathrm{made}}$	83			ac	73	que	$\operatorname{stion}$	65	
send	146	de	96		part	83	- 11	1	today	73		aply	65	
free	144	money	94	11	cluding	81	- 11	ir	nterest	72		ffer	63	
make	140	message	91	r	nailing	81	.    (	qu	estions	72	rece	eived	63	
email	133	word	91		type	80	)	r	emove	72	ger	neral	63	
1 1	100	1 11	1 00	11		I	. 11		. 1	— I	1 1	,	1 00 1	

web

give

program

place

date

john

related

found

linguist

usa

data

important

ca

summary

long

number

work

www

languages

find

 $\operatorname{check}$ 

phone

receive

 $\operatorname{good}$ 

COMP3608 Naïve Bayes

# Subject vs Body: Results and Discussion

Corpus: Subject					
	Accuracy [%]				
ZeroR					
OneR					
1-NN					
3-NN					
NB					
DT					
MLP					
MyNB					

-	
Corpus:	Body
	Accuracy [%]
ZeroR	
OneR	
1-NN	
3-NN	
NB	
DT	
MLP	
MyNB	

# Challenge Results and Discussion

### Conclusions

The tokens used in our classifier are formed from single words. Therefore, it will not analyse common consecutive words that are found in spam emails, leading to the failure of our classifier from detecting these emails.

By taking into account permutations of consecutive words, or words that appear within a specified distance of each other, the accuracy of our Bayesian classifier could be increased.

### Reflection

Instructions: How to run code