CS7611-COMPILER LABORATORY NEWS CLASSIFICATION

Submitted by:

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Problem statement:

Classifying the news based on the headlines.

Languages used:

Lex, python.

Github link:

https://github.com/VarshaAnandavel/Varsha

Implementation details:

We have implemented in both python and lex. In lex implementation, the input is read from a file and the output will be the news and the category to which it belongs to. Ie, if the news is related to politics, 'political' will be displayed. We have also displayed the total number of news in each category. Using python, we have displayed the number of news in each category provided with a dataset. The precision and accuracy will also be displayed.

Output:

Output of lex code:

```
yersha@varsha.pc:-$ ./a.out

if lie did view Search Terminal Help

varsha@varsha.pc:-$ ./a.out

if the catched the nan who knowload in robbery. -- news related to robbery

they catched the nan who knowload in robbery. -- news related to robbery

they catched the nan who knowload in robbery. -- news related to robbery

behit fair price shop owner arrested for swindling food grains. -- crine news

Doctors found medicine for corona. -- nedical news

ocronavirus in India: Doctor treating 14 Italian tourists gives a peek into behind-the-scene. -- nedical news

Trump holds support of political base in virus-prone states. -- political news

Haryana ana confesses to Tirupur bank robbery. -- news related to robbery

which appears the statistic points fingers after ban violation reports.

which is a ports intister points fingers after ban violation reports.

whiscensin set to hold in-person voting in presidential primary. -- political news

"harkanaic Minor girl accuses friend, 8 others of rape in Dunka. -- crine news

and the state of the
```

Output of python code:

	@varsha-pc: ~/Desktor File Edit View Search				
	accuracy	reminde riep		0.49	594
	macro avq	0.47	0.50	0.47	594
	weighted avg	0.55	0.49	0.50	594
	Training Random For				
		precision	recall	f1-score	support
	Business & Finance	0.37	0.49	0.42	88
	Criminal Justice	0.35	0.51	0.41	
٩	Health Care	0.48	0.70	0.57	66
d	Politics & Policy	0.77	0.49	0.60	261
ij	Science & Health	0.55	0.57	0.56	108
ľ	accuracy			0.53	594
ā	macro avg	0.50	0.55	0.51	594
į	weighted avg	0.59	0.53	0.54	594
Á	Training Multinomia	al Naive Baye	sian		
		precision	recall	f1-score	support
	Business & Finance	0.51	0.58	0.54	88
	Criminal Justice	0.51	0.52	0.51	71
	Health Care	0.49	0.64	0.56	66
	Politics & Policy	0.74	0.60	0.66	261
	Science & Health	0.60	0.69	0.64	108
	accuracy			0.61	594
	macro avg	0.57	0.60	0.58	594
	weighted avg	0.62	0.61	0.61	594
	Training Support Ve				
		precision	recall	f1-score	support
	Business & Finance	0.44	0.27	0.34	88
	Criminal Justice	0.41	0.10	0.16	71
	Health Care	0.56	0.29	0.38	66
	Politics & Policy	0.53	0.88	0.66	261
	Science & Health	0.61	0.32	0.42	108
	accuracy			0.53	594
7	macro avg	0.51	0.37	0.39	594
2	weighted avg	0.52	0.53	0.48	594

	Science & Health	0.61	0.32	0.42	108
	accuracy macro avo	0.51	0.37	0.53	594 594
٠	macro avg weighted avg	0.51	0.57	0.39	594 594
	weighted avg	0.52	0.55	0.48	594
i	Training Multilayer		n		
		precision	recall	f1-score	support
	Business & Finance	0.52	0.45	0.48	88
0	Criminal Justice	0.49	0.46	0.48	71
=	Health Care	0.42	0.42	0.42	66
	Politics & Policy	0.67	0.68	0.67	261
V	Science & Health	0.57	0.62	0.59	108
	Secence a neacci	0.57	0.02		100
	1 accuracy			0.58	594
=	macro avg	0.53	0.53	0.53	594
	weighted avg	0.58	0.58	0.58	594
	Predicting test data				
		precision	recall	f1-score	support
	Business & Finance	0.39	0.51	0.44	97
	Criminal Justice	0.67	0.57	0.61	99
	Health Care	0.47	0.62	0.54	90
	Politics & Policy	0.73	0.62	0.67	333
	Science & Health	0.62	0.65	0.64	173
	accuracy			0.61	792
	accuracy macro avg weighted avg	0.58 0.63	0.59 0.61	0.61 0.58 0.61	792 792 792