20 NEWS GROUP CLASSIFICATION

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PIPELINE

20 NEWSGROUPS DATASET PREPROCESSING · Conversione testo in minuscolo Eliminazione indirizzi mail Eliminazione dei numeri Eliminazione caratteri di punteggiatura · Rimozione parole composte da una e due lettere · Sistemazione degli spazi creati con le precedenti operazioni Tokenizzazione · Rimozione stop words Stemming Stemming Stemming Lemmatization (Porter) (Snowball) (Lancaster) TRAIN SET (60%) TEST SET (40%) TF TF TF • TF TF-IDF UNIGRAM TF-IDF UNIGRAM TF-IDF UNIGRAM TF-IDF UNIGRAM TF-IDF UNI+BIGRAM . TF-IDF UNI+BIGRAM TF-IDF UNI+BIGRAM TF-IDF UNI+BIGRAM TEXT REPRESENTATION NAIVE BAYES SVM RANDOM FOREST XGBOOST CLASSIFICATION

DATASET 20 NEWSGROUPS

19997 documenti divisi in 20 newsgroups:

- 1. alt.atheism
- 2. comp.graphics
- 3. comp.os.ms-windows.misc
- 4. comp.sys.ibm.pc.hardware
- 5. comp.sys.mac.hardware
- 6. comp.windows.x
- 7. misc.forsale
- 8. rec.autos
- 9. rec.motorcycles
- 10.rec.sport.baseball

- 11. rec.sport.hockey
- 12. sci. crypt
- 13. sci.electronics
- 14. sci. med
- 15. sci. space
- 16. soc.religion.christian
- 17. talk.politics.guns
- 18. talk.politics.mideast
- 19. talk.politics.misc
- 20. talk.religion.misc

PREPROCESSING

- Conversione testo in minuscolo
- Eliminazione indirizzi mail
- Eliminazione dei numeri
- Eliminazione caratteri di punteggiatura
- Rimozione parole composte da una e due lettere
- Sistemazione degli spazi creati con le precedenti operazioni
- Tokenizzazione
- Rimozione Stop Words
- Lemmatization
- Stemming: Porter, Snowball, Lancaster

Dataset diviso in Training set (60%) e Test set (40%)

TEXT REPRESENTATION

- Term Frequency (TF): la Term Frequency tft,d del termine t nel doumento d è definito come il numero di volte che t si verifica in d
- Term Frequency-Inverse Document Frequency (TF-IDF): il peso tf-idf di un termine è il prodotto del suo peso tf e del suo peso idf
 - Unigram
 - Unigram + Bigram

Matrici costruite per:

- Dati lemmatizzati
- Dati stemmatizzati (Porter)
- Dati stemmatizzati (Snowball)
- Dati stemmatizzati (Lancaster)

→ 24 Matrici (12 Train + 12 Test)

TEXT CLASSIFICATION

- Multinomial NB
- SVM
- Random Forest
- XGBOOST

MULTINOMIAL NAIVE BAYES

	TRAIN (cro	ss validation)	TE	T				
	Accuracy	Time	Accuracy	Time				
TF + LEM	0.86	395 ms	0.87	119 ms				
TF + STEM (Porter)	0.85	320 ms	0.86	207 ms				
TF + STEM (Snowball)	0.85	319 ms	0.86	96.4 ms				
TF + STEM (Lancaster)	0.85	304 ms	0.85	99.5 ms				
TF-IDF + LEM	0.86	228 ms	0.87	76.8 ms				
TF-IDF + STEM (Porter)	0.85	220 ms	0.86	72.9 ms				
TF-IDF + STEM (Snowball)	0.85	211 ms	0.86	78.7 ms				
TF-IDF + STEM (Lancaster)	0.85	245 ms	0.86	95.2 ms				
TF-IDF (bigram) + LEM	0.86	235 ms	0.87	84.2 ms				
TF-IDF (bigram) + STEM (Porter)	0.86	250 ms	0.87	84.6 ms				
TF-IDF (bigram) + STEM (Snowball)	0.86	240 ms	0.87	82 ms				
TF-IDF (bigram) + STEM (Lancaster)	0.86	244 ms	0.86	86.2 ms				

SUPPORT VECTOR MACHINE (SVM)

	TRAIN (cros	ss validation)	TE	ST				
12	Accuracy	Time	Accuracy	Time				
TF + LEM	0.75	8 min 39 s	0.78	3 min 11 s				
TF + STEM (Porter)	0.75	8 min 19 s	0.78	3 min 5 s				
TF + STEM (Snowball)	0.75	8 min 42 s	0.78	3 min 29 s				
TF + STEM (Lancaster)	0.74	8 min 38 s	0.77	3 min 6 s				
TF-IDF + LEM	0.89	12 min 10 s	0.90	4 min 47 s				
TF-IDF + STEM (Porter)	0.89	12 min 44 s	0.90	4 min 23 s				
TF-IDF + STEM (Snowball)	0.89	11 min 47 s	0.90	4 min 17 s				
TF-IDF + STEM (Lancaster)	0.88	11 min 45 s	0.89	4 min 14 s				
TF-IDF (bigram) + LEM	0.89	14 min 25 s	0.90	4 min 57 s				
TF-IDF (bigram) + STEM (Porter)	0.89	14 min 12 s	0.90	5 min 3 s				
TF-IDF (bigram) + STEM (Snowball)	0.89	13 min 55 s	0.90	4 min 56 s				
TF-IDF (bigram) + STEM (Lancaster)	0.89	13 min 43 s	0.89	4 min 50 s				

RANDOM FOREST

	TRAIN (cros	ss validation)	TE	ST .				
	Accuracy	Time	Accuracy	Time				
TF + LEM	0.83	2 min 37 s	0.84	31.9 s				
TF + STEM (Porter)	0.82	2 min 23 s	0.84	29.4 s				
TF + STEM (Snowball)	0.82	2 min 21 s	0.84	29.4 s				
TF + STEM (Lancaster)	0.81	2 min 13 s	0.83	28.6 s				
TF-IDF + LEM	0.81	1 min 29 s	0.83	23.3 s				
TF-IDF + STEM (Porter)	0.81	1 min 31 s	0.83	22.9 s				
TF-IDF + STEM (Snowball)	0.81	1 min 31 s	0.82	23.2 s				
TF-IDF + STEM (Lancaster)	0.80	1 min 35 s	0.82	25.1 s				
TF-IDF (bigram) + LEM	0.81	1 min 34 s	0.83	25.4 s				
TF-IDF (bigram) + STEM (Porter)	0.82	1 min 33 s	0.83	25.2 s				
TF-IDF (bigram) + STEM (Snowball)	0.81	1 min 33 s	0.83	25.5 s				
TF-IDF (bigram) + STEM (Lancaster)	0.80	1 min 35 s	0.82	25.5 s				

XGBOOST

	TRAIN (cros	ss validation)	TE	ST				
	Accuracy	Time	Accuracy	Time				
TF + LEM	0.80	16 min 42 s	0.80	3 min 34 s				
TF + STEM (Porter)	0.80	14 min 14 s	0.79	3 min 3 s				
TF + STEM (Snowball)	0.80	13 min 38 s	min 38 s 0.79					
TF + STEM (Lancaster)	0.79	12 min 36 s	0.79	2 min 45 s				
TF-IDF + LEM	0.79	13 min 54 s	0.79	3 min 25 s				
TF-IDF + STEM (Porter)	0.79	14 min 26 s	0.79	3 min 27 s				
TF-IDF + STEM (Snowball)	0.79	14 min 16 s	0.79	3 min 27 s				
TF-IDF + STEM (Lancaster)	0.78	14 min 1 s	0.78	3 min 25 s				
TF-IDF (bigram) + LEM	0.79	15 min 26 s	0.80	3 min 50 s				
TF-IDF (bigram) + STEM (Porter)	0.80	15 min 45 s	0.80	3 min 51 s				
TF-IDF (bigram) + STEM (Snowball)	0.79	15 min 47 s	0.80	3 min 55 s				
TF-IDF (bigram) + STEM (Lancaster)	0.79	16 min 10 s	0.79	3 min 59 s				

CONCLUSIONI

Il modello migliore in termini di *Recall, Precision* ed *F1-score* risulta essere *Support Vector Machine* nelle rappresentazioni tf-idf

	precision	recall	f1-score	support	0	295	0	0	0	0	0	0	1	0	0	0	0	1	4	1	16	0	0	1	21		
0	0.92	0.87	0.89	340	д.	- 0	336	8	8	2	8	2	0	0	1	0	0	7	2	0	0	0	0	0	0		75.0
1	0.71	0.90	0.80	374	7	- 0	26	329	22	5	9	2	0	0	0	0	0	6	0	1	0	0	0	0	0	_	350
2	0.86	0.82	0.84	400		. 1	21	19	314	10	1	q	2	0	0	0	1	14	0	0	0	0	0	0	1		
3	0.79	0.80	0.79	393								_	-	-		-	_	14		-	-	-	-				
4	0.89	0.88	0.89	358	4	- 0	8	5	13	314	4	8	0	0	1	0	0	4	1	0	0	0	0	0	0	-	300
5	0.91	0.88	0.90	416	r)	- 0	25	11	5	1	368	0	1	0	0	0	0	3	0	1	0	0	0	1	0		
6	0.85	0.88	0.87	386	9 -	- 0	2	3	11	7	0	340	11	1	0	3	0	7	1	0	0	0	0	0	0		
7	0.92	0.89	0.91	396	_	. 0	6	2	1	3	2	6	354	7	1	0	0	11	1	2	0	0	0	0	0	-	250
8	0.97	0.95	0.96	393			_	-	_		-									_							
9	0.97	0.96	0.96	405	ω .	- 0	2	0	0	0	0	8	4	373	0	0	0	4	1	0	0	0	0	1	0		
10	0.99	0.96	0.97	386	la e	- 0	3	0	1	1	0	6	1	1	389	1	0	2	0	0	0	0	0	0	0	_	200
11	0.99	0.92	0.96	400	Actual	- 0	2	0	2	1	2	1	1	0	3	370	0	2	2	0	0	0	0	0	0		
12	0.81	0.89	0.85	406		٥	13	2	٥	1	4	٥	٥	٥	0	٥	369	5	٥	٥	1	2	٥	3	0		
13	0.90	0.95	0.92	380	Ξ.	- 0	13	- 2	U	1	4	U	U	U	-	U				U	1	2	U	,			150
14	0.98	0.93	0.95	403	12	- 0	7	1	19	3	0	6	5	0	0	0	0	362	2	1	0	0	0	0	0		150
15	0.89	0.94	0.91	391	Ξ.	- 2	4	0	0	0	0	3	1	0	2	0	0	7	360	0	0	1	0	0	0		
16	0.91	0.92	0.91	380		- 0	9	0	0	0	3	2	1	0	0	0	0	5	7	373	0	1	0	2	0		
17	0.99	0.96	0.98	399		_	0	^	۸	,	1	٥	٥	۸	2	٥	۸	2	6	0	367	0	,	2	0	-	100
18	0.87	0.87	0.87	285	15	- 9	U	U	U	1	1	U	U	U	2	U	U	2	0	U			1				
19	0.88	0.71	0.78	248	16	- 0	1	0	0	0	0	3	1	0	0	0	1	2	1	1	0	348	1	19	2		
					5	- 1	4	0	1	0	2	0	0	1	0	0	0	0	2	0	1	0	385	2	0	-	50
accuracy			0.90	7539	. 8	_	0	1	0	1	0	2	2	1	3	0	1	1	5	1	2	16	1	247	0		
macro avg	0.90	0.89	0.90	7539			,	_	^	,	^	,	,	_	_	^	_	2	_	,	25	10	,		175		
weighted avg	0.90	0.90	0.90	7539	13	- 13	1	0	0	Ţ	0	1	1	0	0	0	0	2	5	1	25	16	1	ь	1/5	_	0
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															Predi	icted	1										

GRAZIE PER L'ATTENZIONE