20 NEWS GROUP CLASSIFICATION

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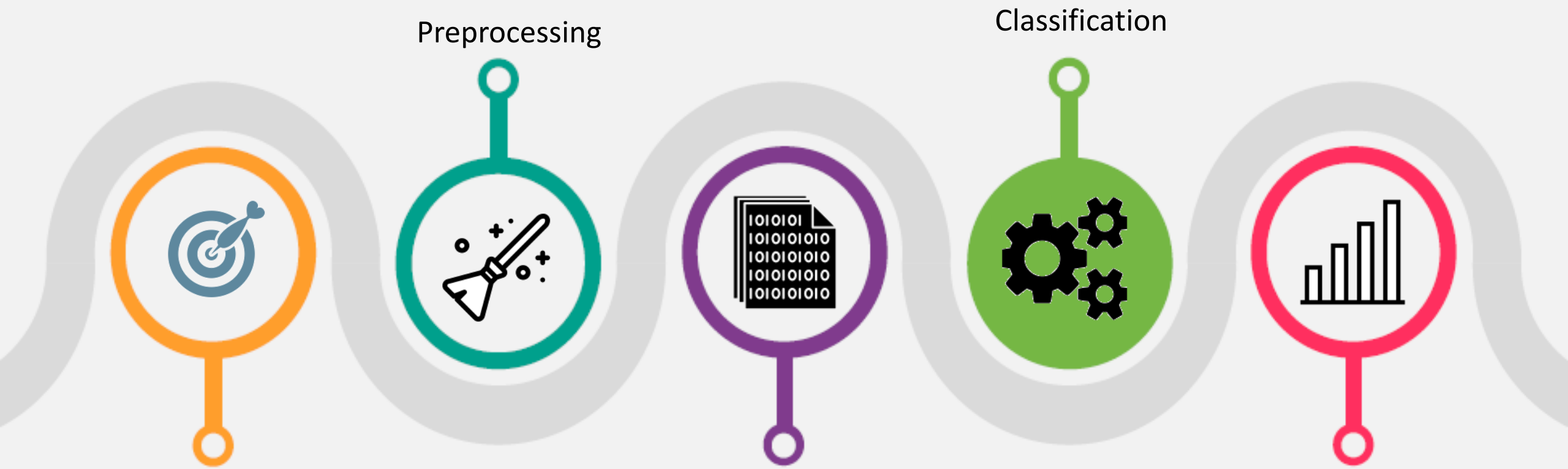
PIPELINE


Preprocessing
Classification
Obiettivo
Text Representation
Evaluation

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

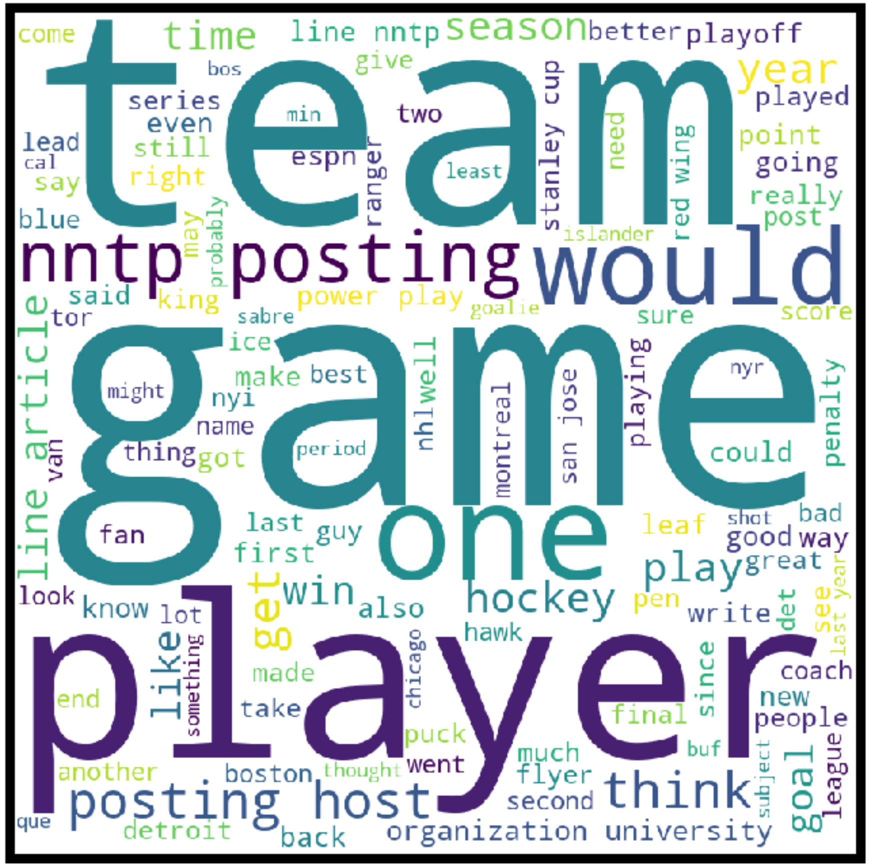
Obiettivo: Text Classification

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%)

WORDCLOUD


team
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player
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red wing
hockey
play
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organization university
win
article
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fan
last
first
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also
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power play
sure
score
could
penalty
montreal
san jose
playing
nhl
well
best
make
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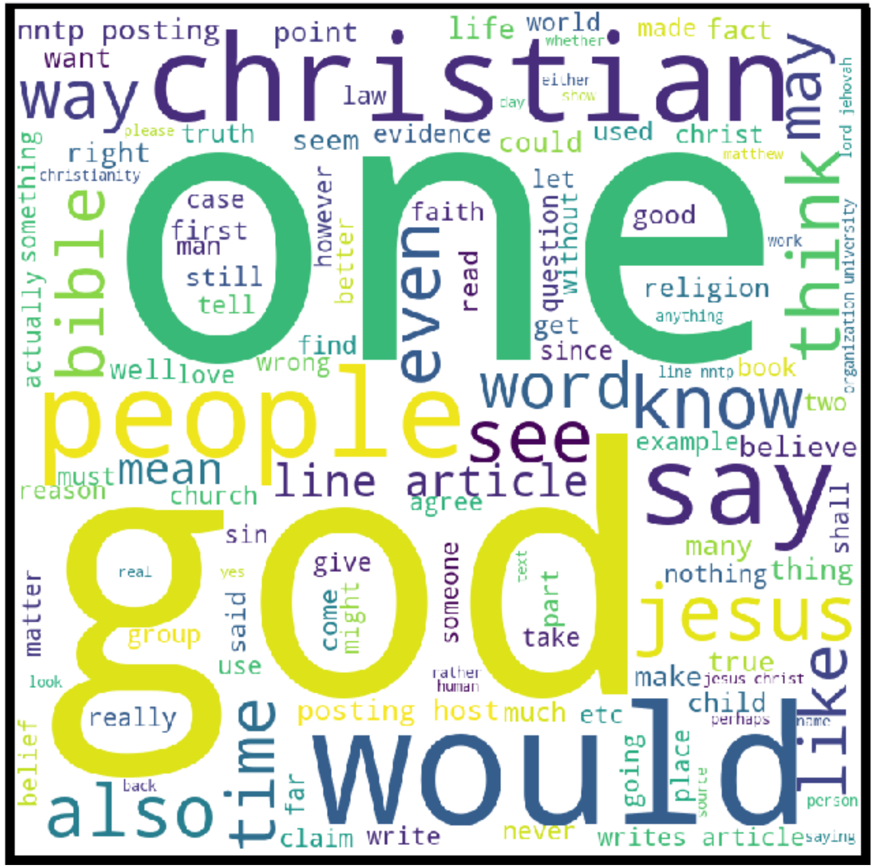
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truth
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either
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matthew
work
text

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 (cross validation)		TEST	
	Accuracy	Time	Accuracy	Time
TF + LEM	0.86	383 ms	0.87	127 ms
TF + STEM (Porter)	0.85	351 ms	0.86	106 ms
TF + STEM (Snowball)	0.85	345 ms	0.86	113 ms
TF + STEM (Lancaster)	0.85	306 ms	0.85	111 ms
TF-IDF + LEM	0.86	252 ms	0.87	77.6 ms
TF-IDF + STEM (Porter)	0.85	215 ms	0.86	77.7 ms
TF-IDF + STEM (Snowball)	0.85	223 ms	0.86	77.3 ms
TF-IDF + STEM (Lancaster)	0.85	222 ms	0.86	76.6 ms
TF-IDF (bigram) + LEM	0.86	262 ms	0.87	101 ms
TF-IDF (bigram) + STEM (Porter)	0.86	267 ms	0.87	88.7 ms
TF-IDF (bigram) + STEM (Snowball)	0.86	261 ms	0.87	89.8 ms
TF-IDF (bigram) + STEM (Lancaster)	0.86	247 ms	0.86	88.2 ms

SUPPORT VECTOR MACHINE (SVM)

	TRAIN (cross validation)		TEST	
	Accuracy	Time	Accuracy	Time
TF + LEM	0.75	9 min 10 s	0.78	3 min 29 s
TF + STEM (Porter)	0.75	8 min 52 s	0.78	3 min 28 s
TF + STEM (Snowball)	0.75	8 min 55 s	0.78	3 min 27 s
TF + STEM (Lancaster)	0.74	8 min 37 s	0.77	3 min 20 s
TF-IDF + LEM	0.89	12 min 40 s	0.90	4 min 35 s
TF-IDF + STEM (Porter)	0.89	12 min 40 s	0.90	4 min 34 s
TF-IDF + STEM (Snowball)	0.89	12 min 27 s	0.90	4 min 29 s
TF-IDF + STEM (Lancaster)	0.88	12 min 26 s	0.89	4 min 18 s
TF-IDF (bigram) + LEM	0.89	14 min 12 s	0.90	5 min 4 s
TF-IDF (bigram) + STEM (Porter)	0.89	14 min 34 s	0.90	5 min 10 s
TF-IDF (bigram) + STEM (Snowball)	0.89	14 min 5 s	0.90	4 min 59 s
TF-IDF (bigram) + STEM (Lancaster)	0.89	13 min 44 s	0.89	5 min

RANDOM FOREST

	TRAIN (cross validation)		TEST	
	Accuracy	Time	Accuracy	Time
TF + LEM	0.83	2 min 46 s	0.84	32.6 s
TF + STEM (Porter)	0.82	2 min 25 s	0.84	30.6 s
TF + STEM (Snowball)	0.82	2 min 25 s	0.84	29.9 s
TF + STEM (Lancaster)	0.81	2 min 16 s	0.83	29.4 s
TF-IDF + LEM	0.82	1 min 31 s	0.83	23.8 s
TF-IDF + STEM (Porter)	0.81	1 min 33 s	0.83	23.7 s
TF-IDF + STEM (Snowball)	0.81	1 min 34 s	0.83	23.7 s
TF-IDF + STEM (Lancaster)	0.80	1 min 40 s	0.82	24.3 s
TF-IDF (bigram) + LEM	0.82	1 min 31 s	0.83	24.5 s
TF-IDF (bigram) + STEM (Porter)	0.81	1 min 31 s	0.83	24.8 s
TF-IDF (bigram) + STEM (Snowball)	0.82	1 min 31 s	0.83	24.4 s
TF-IDF (bigram) + STEM (Lancaster)	0.81	1 min 33 s	0.82	24.9 s

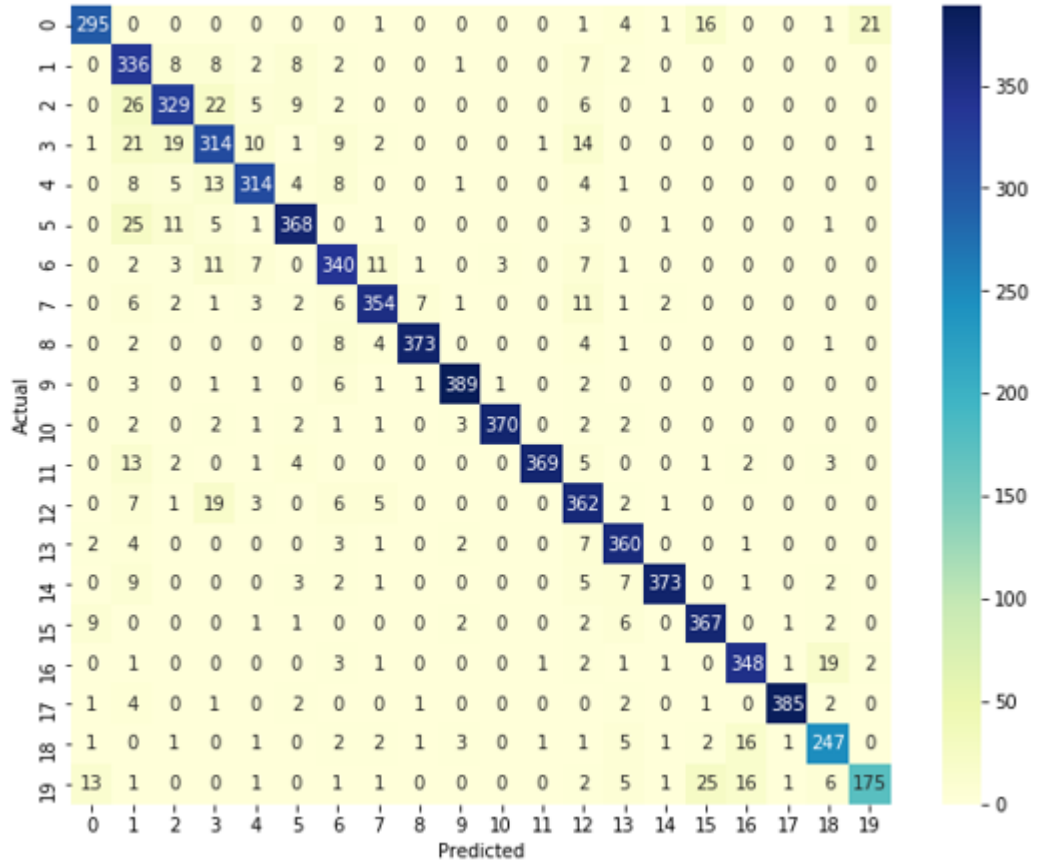
XGBOOST

	TRAIN (cross validation)		TEST	
	Accuracy	Time	Accuracy	Time
TF + LEM	0.80	15 min 44 s	0.80	3 min 20 s
TF + STEM (Porter)	0.80	13 min 33 s	0.79	2 min 58 s
TF + STEM (Snowball)	0.79	13 min 24 s	0.79	2 min 56 s
TF + STEM (Lancaster)	0.78	12 min 10 s	0.79	2 min 40 s
TF-IDF + LEM	0.79	13 min 33 s	0.79	3 min 20 s
TF-IDF + STEM (Porter)	0.79	13 min 58 s	0.79	3 min 27 s
TF-IDF + STEM (Snowball)	0.79	14 min 14 s	0.79	3 min 30 s
TF-IDF + STEM (Lancaster)	0.78	14 min 25 s	0.78	3 min 32 s
TF-IDF (bigram) + LEM	0.80	15 min 32 s	0.80	3 min 51 s
TF-IDF (bigram) + STEM (Porter)	0.80	15 min 45 s	0.80	3 min 49 s
TF-IDF (bigram) + STEM (Snowball)	0.80	15 min 30 s	0.80	3 min 49 s
TF-IDF (bigram) + STEM (Lancaster)	0.79	15 min 42 s	0.79	3 min 53 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	0.92	0.87	0.89	340
1	0.71	0.90	0.80	374
2	0.86	0.82	0.84	400
3	0.79	0.80	0.79	393
4	0.89	0.88	0.89	358
5	0.91	0.88	0.90	416
6	0.85	0.88	0.87	386
7	0.92	0.89	0.91	396
8	0.97	0.95	0.96	393
9	0.97	0.96	0.96	405
10	0.99	0.96	0.97	386
11	0.99	0.92	0.96	400
12	0.81	0.89	0.85	406
13	0.90	0.95	0.92	380
14	0.98	0.93	0.95	403
15	0.89	0.94	0.91	391
16	0.91	0.92	0.91	380
17	0.99	0.96	0.98	399
18	0.87	0.87	0.87	285
19	0.88	0.71	0.78	248
accuracy			0.90	7539
macro avg	0.90	0.89	0.90	7539
weighted avg	0.90	0.90	0.90	7539



GRAZIE PER L’ATTENZIONE