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Pour en finir avec le pré-traitement des données textuelles ?

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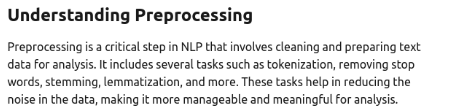
Sorbonne Université

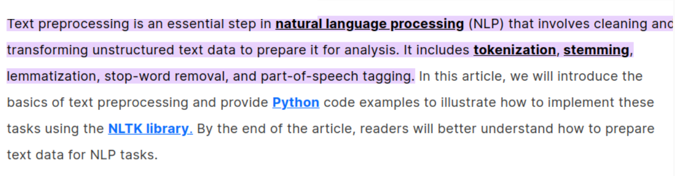
Preprocessing in NLP, what is it good for ?

The dogma

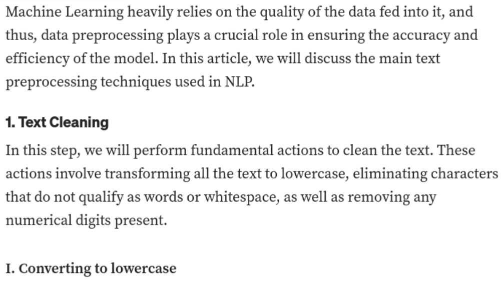


Understanding Preprocessing

Preprocessing is a critical step in NLP that involves cleaning and preparing text data for analysis. It includes several tasks such as tokenization, removing stop words, stemming, lemmatization, and more. These tasks help in reducing the noise in the data, making it more manageable and meaningful for analysis.



Text preprocessing is an essential step in **natural language processing** (NLP) that involves cleaning and transforming unstructured text data to prepare it for analysis. It includes **tokenization**, **stemming**, lemmatization, stop-word removal, and part-of-speech tagging. In this article, we will introduce the basics of text preprocessing and provide **Python** code examples to illustrate how to implement these tasks using the **NLTK library.** By the end of the article, readers will better understand how to prepare text data for NLP tasks.

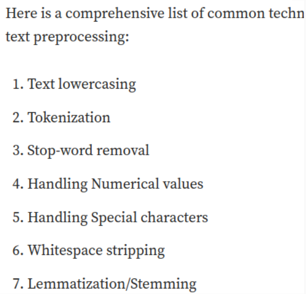


Machine Learning heavily relies on the quality of the data fed into it, and thus, data preprocessing plays a crucial role in ensuring the accuracy and efficiency of the model. In this article, we will discuss the main text preprocessing techniques used in NLP.

1. Text Cleaning

In this step, we will perform fundamental actions to clean the text. These actions involve transforming all the text to lowercase, eliminating characters that do not qualify as words or whitespace, as well as removing any numerical digits present.

I. Converting to lowercase



Here is a comprehensive list of common techn text preprocessing:

1. Text lowercasing
2. Tokenization
3. Stop-word removal
4. Handling Numerical values
5. Handling Special characters
6. Whitespace stripping
7. Lemmatization/Stemming

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- Do they focus attention on the right problems ?

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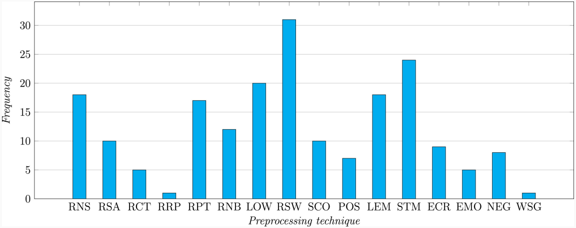
How good is your tokenizer ? on the monolingual performance of multilingual language models [Rust et al., 2020]

Stemming impact on arabic text categorization performance : A survey (Al Anzi 2015)

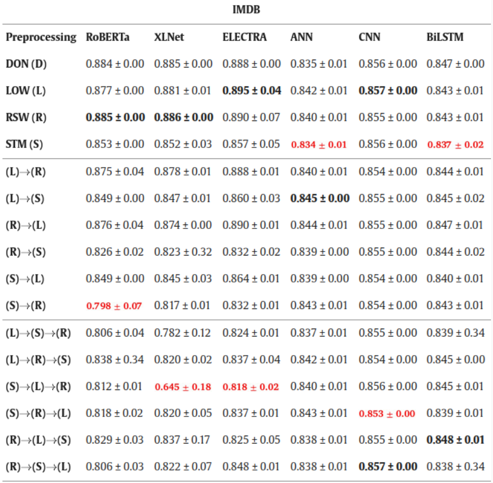
Is text preprocessing still worth the time ? A comparative survey on the influence of popular preprocessing methods . . . [Siino et al., 2024]

A more detailed overview (Siino et al.)



DON	Do Nothing
RNS	Replace Noise
RSA	Replace Slang/Abbreviations
RCT	Replace Contraction
RRP	Remove Repeated Punctuation
RPT	Removing Punctuation
RNB	Remove Numbers
LOW	Lowercasing
RSW	Remove Stop Words
SCO	Spelling Correction
POS	Part-of-Speech Tagging
LEM	Lemmatization
STM	Stemming
ECR	Remove Elongation
EMO	Emoticon Handling
NEG	Negation Handling
WSG	Word Segmentation (some trending topic)

Sentiment on Reviews `en` [Siino et al., 2024]



IMDB

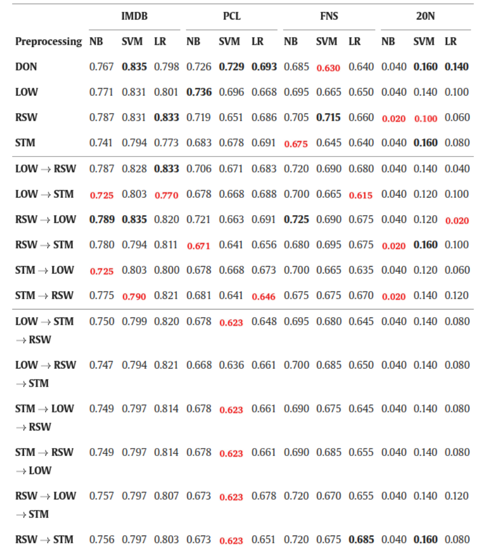
Preprocessing	RoBERTa	XLNet	ELECTRA	ANN	CNN	BiLSTM
DON (D)	0.884 ± 0.00	0.885 ± 0.00	0.888 ± 0.00	0.835 ± 0.01	0.856 ± 0.00	0.847 ± 0.00
LOW (L)	0.877 ± 0.00	0.881 ± 0.01	**0.895 ± 0.04**	0.842 ± 0.01	**0.857 ± 0.00**	0.843 ± 0.01
RSW (R)	**0.885 ± 0.00**	**0.886 ± 0.00**	0.890 ± 0.07	0.840 ± 0.01	0.855 ± 0.00	0.843 ± 0.01
STM (S)	0.853 ± 0.00	0.852 ± 0.03	0.857 ± 0.05	0.834 ± 0.01	0.856 ± 0.00	0.837 ± 0.02
(L)→(R)	0.875 ± 0.04	0.878 ± 0.01	0.888 ± 0.01	0.840 ± 0.01	0.854 ± 0.00	0.844 ± 0.01
(L)→(S)	0.849 ± 0.00	0.847 ± 0.01	0.860 ± 0.03	**0.845 ± 0.00**	0.855 ± 0.00	0.845 ± 0.02
(R)→(L)	0.876 ± 0.04	0.874 ± 0.00	0.890 ± 0.01	0.844 ± 0.01	0.855 ± 0.00	0.847 ± 0.01
(R)→(S)	0.826 ± 0.02	0.823 ± 0.32	0.832 ± 0.02	0.839 ± 0.00	0.855 ± 0.00	0.844 ± 0.02
(S)→(L)	0.849 ± 0.00	0.845 ± 0.03	0.864 ± 0.01	0.839 ± 0.00	0.854 ± 0.00	0.840 ± 0.01
(S)→(R)	0.798 ± 0.07	0.817 ± 0.01	0.832 ± 0.01	0.843 ± 0.01	0.854 ± 0.00	0.843 ± 0.01
(L)→(S)→(R)	0.806 ± 0.04	0.782 ± 0.12	0.824 ± 0.01	0.837 ± 0.01	0.855 ± 0.00	0.839 ± 0.34
(L)→(R)→(S)	0.838 ± 0.34	0.820 ± 0.02	0.837 ± 0.04	0.842 ± 0.01	0.854 ± 0.00	0.845 ± 0.00
(S)→(L)→(R)	0.812 ± 0.01	0.645 ± 0.18	0.818 ± 0.02	0.840 ± 0.01	0.856 ± 0.00	0.845 ± 0.01
(S)→(R)→(L)	0.818 ± 0.02	0.820 ± 0.05	0.837 ± 0.01	0.843 ± 0.01	0.853 ± 0.00	0.839 ± 0.01
(R)→(L)→(S)	0.829 ± 0.03	0.837 ± 0.17	0.825 ± 0.05	0.838 ± 0.01	0.855 ± 0.00	**0.848 ± 0.01**
(R)→(S)→(L)	0.806 ± 0.03	0.822 ± 0.07	0.848 ± 0.01	0.838 ± 0.01	**0.857 ± 0.00**	0.838 ± 0.34

Figure 1 – Median accuracy over 5 runs + max difference. For each model, the best result is in bold, the worst in red.

A more detailed overview (en) (Siino et al.)

IMDB : Review Polarity, PCL : Press Condescending Language

FNS : Fake News, 20N : Forum Categorization



	IMDB			PCL			FNS			20N		
Preprocessing	**NB**	**SVM**	**LR**	**NB**	**SVM**	**LR**	**NB**	**SVM**	**LR**	**NB**	**SVM**	**LR**
DON	0.767	**0.835**	0.798	0.726	**0.729**	**0.693**	0.685	0.630	0.640	0.040	**0.160**	**0.140**
LOW	0.771	0.831	0.801	**0.736**	0.696	0.668	0.695	0.665	0.650	0.040	0.140	0.100
RSW	0.787	0.831	**0.833**	0.719	0.651	0.686	0.705	**0.715**	0.660	0.020	0.100	0.060
STM	0.741	0.794	0.773	0.683	0.678	0.691	0.675	0.645	0.640	0.040	**0.160**	0.080
LOW → RSW	0.787	0.828	**0.833**	0.706	0.671	0.683	0.720	0.690	0.680	0.040	0.140	0.040
LOW → STM	0.725	0.803	0.770	0.678	0.668	0.688	0.700	0.665	0.615	0.040	0.120	0.100
RSW → LOW	**0.789**	**0.835**	0.820	0.721	0.663	0.691	**0.725**	0.690	0.675	0.040	0.120	0.020
RSW → STM	0.780	0.794	0.811	0.671	0.641	0.656	0.680	0.695	0.675	0.020	**0.160**	0.100
STM → LOW	0.725	0.803	0.800	0.678	0.668	0.673	0.700	0.665	0.635	0.040	0.120	0.060
STM → RSW	0.775	0.790	0.821	0.681	0.641	0.646	0.675	0.675	0.670	0.020	0.140	0.120
LOW → STM → RSW	0.750	0.799	0.820	0.678	0.623	0.648	0.695	0.680	0.645	0.040	0.140	0.080
LOW → RSW → STM	0.747	0.794	0.821	0.668	0.636	0.661	0.700	0.685	0.650	0.040	0.140	0.080
STM → LOW → RSW	0.749	0.797	0.814	0.678	0.623	0.661	0.690	0.675	0.645	0.040	0.140	0.080
STM → RSW → LOW	0.749	0.797	0.814	0.678	0.623	0.661	0.690	0.685	0.655	0.040	0.140	0.080
RSW → LOW → STM	0.757	0.797	0.807	0.673	0.623	0.678	0.720	0.670	0.655	0.040	0.140	0.120
RSW → STM	0.756	0.797	0.803	0.673	0.623	0.651	0.720	0.675	**0.685**	0.040	**0.160**	0.080

Figurative Language in Tweets `fr` [Choi, 2020]

	Logistic Regression		**Decision Tree**		**MNB**		**KNN**		**Random Forest**	
	Count	**Tfidf**	**Count**	**Tfidf**	**Count**	**Tfidf**	**Count**	**Tfidf**	**Count**	**Tfidf**
DON	**50.20**	**52.03**	**50.41**	**42.89**	**51.42**	**52.24**	**38.82**	**45.73**	**53.25**	**51.22**
RPT	50.41	52.64	48.37	44.72	50.81	51.63	38.21	45.53	**53.05**	**52.64**
RSW	**52.24**	53.86	45.93	44.11	51.22	52.24	37.40	44.31	50.00	50.20
ACC	49.59	52.64	49.39	43.29	51.02	52.03	35.16	45.53	52.44	52.03
URL	**47.56**	**47.36**	**39.43**	**39.43**	**50.20**	**50.61**	**34.35**	**41.46**	**45.53**	**44.51**
LEM	50.20	**54.07**	**49.19**	44.72	**52.24**	**53.25**	**39.02**	45.53	50.41	51.63
STM	51.63	53.86	48.37	**45.93**	52.03	52.44	38.41	**46.75**	52.44	51.42

Table 1 – Average accuracy (in blue : best result, in red : worst result for each classifier)

Figurative Language in Tweets `fr` (Choi 2020)

Classifier	**Count Vectorizer**	**Macro F1-score**	**Tfidf Vectorizer**	**Macro F1-score**
Logistic Regression	LEM, RSW	53.53	LEM, RSW, RAC	54.35
Decision Tree	RPT, accents, RAC, RSW	49.59	RAC, RPT	48.58
MNB	LEM, RSW, RAC	54.59	LEM, RSW, RAC	**55.89**
KNN	RAC, RSW, RPT	**38.20**	RAC, RSW	47.35
Random Forest	LEM, RSW, accents, RAC	51.38	LEM, RSW, accents, RAC	53.25

Table 2 – Best macro F1-scores (in blue : best result, in red : worst result. Best result of DEFT2017 : 65%)

Combinations of preprocessing steps

A comparative evaluation of pre-processing techniques and their interactions for twitter sentiment analysis [Symeonidis et al., 2018]

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What do we learn ?

- Two preprocessing steps can interact negatively
- Performance gains tend to be asymptotic

Combinations of preprocessing steps

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What do we learn ?

- Two preprocessing steps can interact negatively
- Performance gains tend to be asymptotic
- There is no universal "cocktail" that works regardless of :
  - the task
  - the type of texts
  - the classifier
  - the language model

Let's put that in practice

https://github.com/rundimeco/Preprocessing_NLP :

- These slides (PDF)
- A simple notebook illustrating multi-class classification :
- 01_run_experiments_simple_task.ipynb (Kaggle dataset)
- Another example based on a well-known multilingual dataset (corpus_multi.zip) : 02_DiagLang.ipynb
- We then experiment with a different dataset :
- https://www.kaggle.com/datasets/suraj520/multi-task-learning (03_Sentiment_analysis.ipynb)
- The objective is to compare different classifiers and to understand :
  - which preprocessing steps are the most effective
  - how preprocessing effectiveness depends on the classifier
  - how it depends on the task, the type of text, and the language . . .

Choi, H.-S. (2020).

Influence des pré-traitements sur la classification de textes - application à la classification de tweets selon leur polarité.

Master's thesis, Sorbonne Université, France.

Millour, A. (2020).

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Information Systems, 121 :102342.

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Expert Systems with Applications, 110 :298–310.