Do we need pre-processing in NLP ?

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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

Processing or Preprocessing

What is the difference ?

- Preprocessing steps seem harmless (but mandatory ?)
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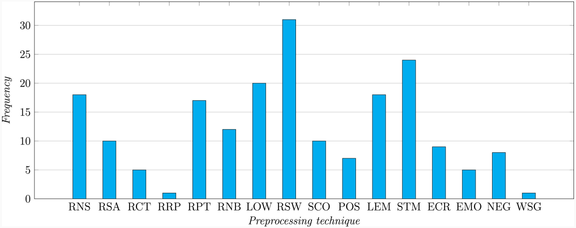
How good is your tokenizer ? on the monolingual performance of multilingual language models [Rust et al., 2020]

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	**SCO**	Spelling Correction
RNS	Replace Noise	**POS**	Part-of-Speech Tagging
RSA	Replace Slang/Abbreviations	**LEM**	Lemmatization
RCT	Replace Contraction	**STM**	Stemming
RRP	Remove Repeated Punctuation	**ECR**	Remove Elongation
RPT	Removing Punctuation	**EMO**	Emoticon Handling
RNB	Remove Numbers	**NEG**	Negation Handling
LOW	Lowercasing	**WSG**	Word Segmentation
RSW	Remove Stop Words		(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

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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 in PDF
- A simple notebook to compare quickly different pre-processing techniques :
- 01_run_experiments_simple_single_task.ipynb (Kaggle dataset)
- Another example with a multilingual task (using corpus_muli.zip)
- Now it's up to you to find the best pre-processing configuration with other multilingual datasets :
- https://www.kaggle.com/datasets/suraj520/multi-task-learning
- https://www.kaggle.com/datasets/azimulh/tweets-data-for-authorship-attribution-modelling
- The objective is to try different classification models (ML, language models) with differ preprocessing configurations in order to find :
- What preprocessing combinations work best
- How much this depends on the learning method

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