



IDENTIFICATION OF TOPICS IN PUBLICATIONS WITH NATURAL LANGUAGE **PROCESSING**

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1 Identification of topics in publications

- 2 Data Pre-processing
- 3 Results

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1 Identification of topics in publications

3 Results

Identification of topics in publications

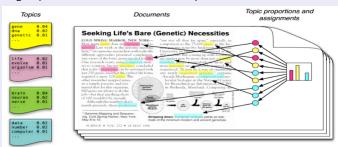
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- Increase user's commitment rate
- Build new hastags
- +200 000 publications
- Topic modeling: unsupervised learning
- Latent Dirichlet Allocation(LDA) and Non-negative matrix factorization(NMF)

Identification of topics in publications

Latent Dirichlet Allocation(LDA)

- Probabilistic model
- Create groups of similar words and find topics



- $\max_{\alpha,\beta} I(\alpha,\beta) = \max_{\alpha,\beta} \sum_{m=1}^{M} logp(w_m | \alpha,\beta)$
 - M: nombre of documents
 - lacksquare α : dirichlet distribution of topics by documents
 - $\blacksquare \beta$: dirichlet distribution of words by topics
 - w: word

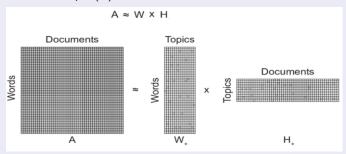
Non-negative matrix factorization(NMF)

Linear algebra model

Identification of topics in publications

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 Decomposition of the word-document matrix(A) into two matrices, the first contains all topics and words(W), and the second contains all documents and topics(H).



 $\min_{W,H>0} \{L(A,WH) + P(W,H)\}\$ with L is the loss function(Kullback Leibler or Frobenius norm) and P is the penalization(L1 or L2)

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Data Pre-processing

Data Pre-processing

- Stopwords
- Outliers: InterQuartile Range method
- Words are lemmatized: words in third person are changed to first person and verbs in past and future tenses are changed into present.

Results •00

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Results

Results: Latent Dirichlet Allocation (LDA)

Topics	Frequency(%)
place-logement-résidence	29.58
ville-quartier-association	29.26
fête-loisirs	22.07
entraide-solidarité	19.09

Results 000

Results

Results: Non-negative matrix factorization(NMF)

Topics	Frequency(%)
entraide-solidarité	46.06
horaire-rendez vous	24.41
fête-loisirs	8.65
avis-communiquer	7.46
transport-déplacement	6.92
qualité de l'air-température	4.68
entretien-environnement	1.82

Conclusion

- Unsupervised learning to identify topics
- Knowing the users' interests
- Build new hastags

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