Utiliser les **connaissances** du **sens commun** pour la découverte de sujets **interprétables**

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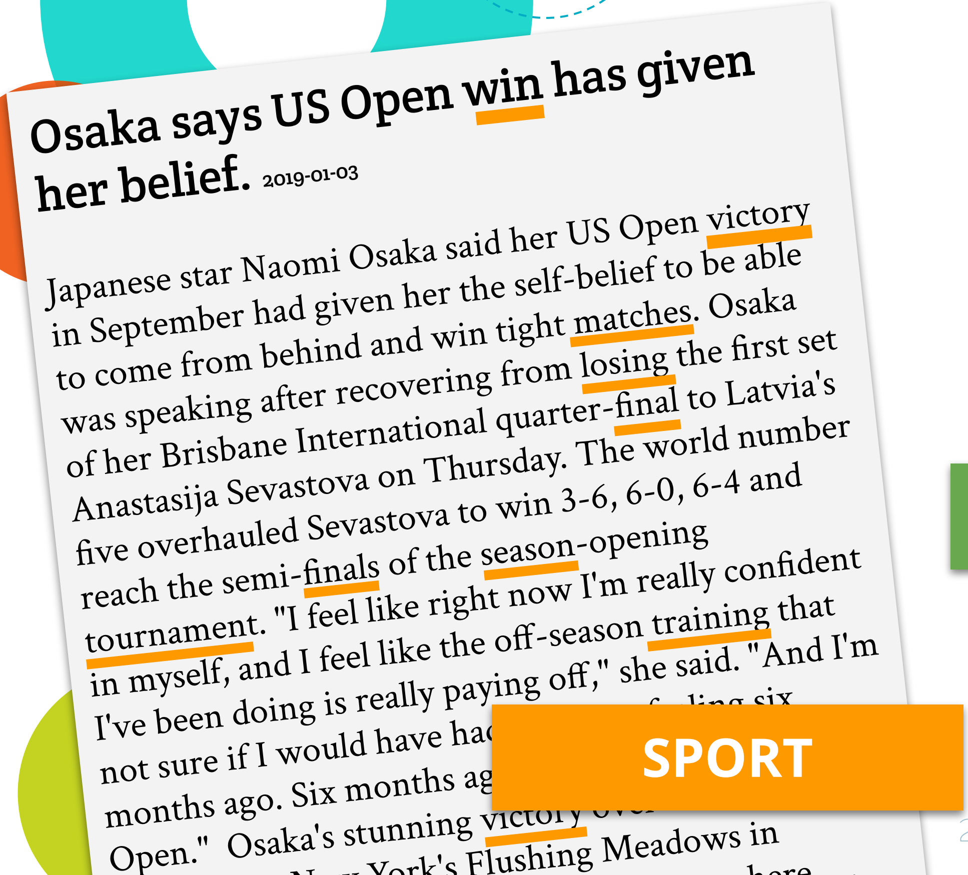
CIMPLE

What is Topic Modeling?



Topic Modeling

Topic Modeling

"Sport"	"Technology"	"Politics"
game	computing	politician
score	hardware	parliament
player	computer	president
match	digital	government
team	internet	election

Using Topic Models

NLP Tasks

- Document retrieval
- Keyword Extraction
- Text Classification
- ..

Accuracy
Precision
Ranking
..

Data Exploration

- Visualization
- Interpretation
- Corpus Analysis
- ..

Coherence?

Different methods

STATISTICAL

Latent Dirichlet Allocation
LDA *Blei et al., 2003*

Hierarchical Dirichlet Process
HDP *Teh et al., 2006*

Gibbs Sampling for a DMM
GSDMM *Yin and Wang, 2014*

EMBEDDING-BASED

Latent Feature Topic Models
LFTM
Nguyen et al., 2015

Paragraph Vector Topic Model
PVTM
Lenz and Winker, 2020

Contextualized Topic Model
CTM
Bianchi et al., 2020

Distributed Representations of Topics
Topic2Vec
Niu and Dai, 2015
Top2Vec
D. Angelov, 2020
BERTopic
M. Grootendorst, 2020

LINEAR ALGEBRA

Latent Semantic Indexing
LSI
Deerwester et al., 1990

Non-negative Matrix Factorisation
NMF
Paatero and Tapper, 1994

NEURAL

doc2topic
D2T
https://github.com/sronnqvist/doc2topic

Evaluating Topic Models

Reading Tea Leaves: How Humans Interpret Topic Models

NeurIPS, 2009

Is Automated Topic Model Evaluation Broken?: The Incoherence of Coherence

NeurIPS, 2021

Topic Model or Topic Twaddle? Re-evaluating Semantic Interpretability Measures

NAACL, 2021

Apples to Apples: A Systematic Evaluation of Topic Models

RANLP, 2021

EURECOM

Coherence?

How to make **topics** more **interpretable**?

Common sense as

Domain Knowledge!

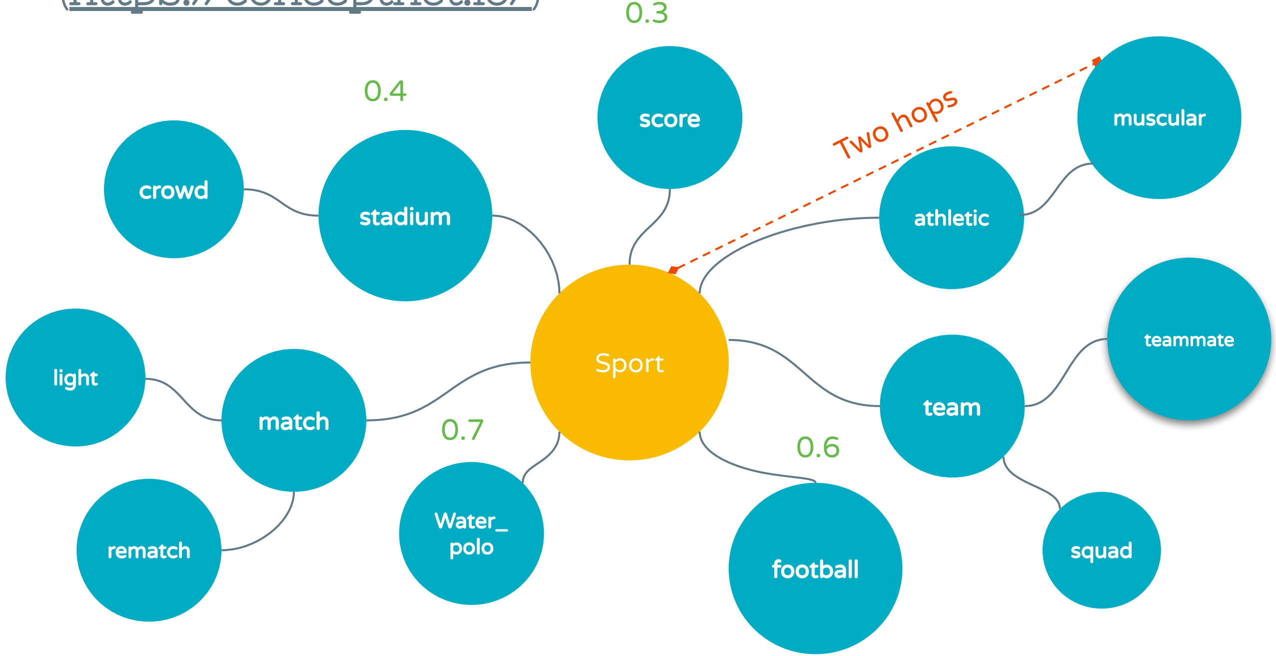
Common Sense Topic Model (CSTM) approach

1. Incorporate **Common Sense Knowledge** into documents

2. Cluster the documents into coherent topics

Common-Sense Knowledge from **ConceptNet**

(https://conceptnet.io/)



Conceptnet 5.5: An open multilingual graph of general knowledge
R. Speer, J. Chin, and C. Havasi. - *Thirty-First AAAI Conference on Artificial Intelligence (AAAI), 2017*

1. Common-Sense enhanced Bag of Words (CS-BoW)

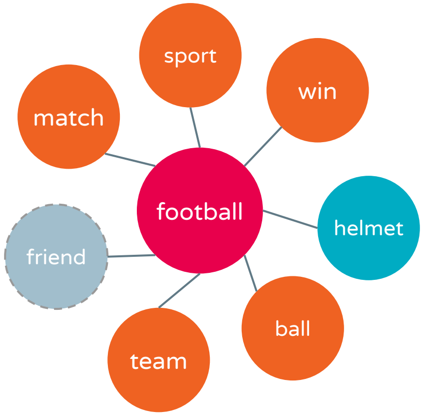
Document

" French team wins **football** championship "

ball	0
championship	1
clown	0
friend	0
football	1
french	1
game	0
match	0
pain	0
peace	0
sport	0
team	1
telephone	0
war	0
win	1

BoW

+*



ConceptNet

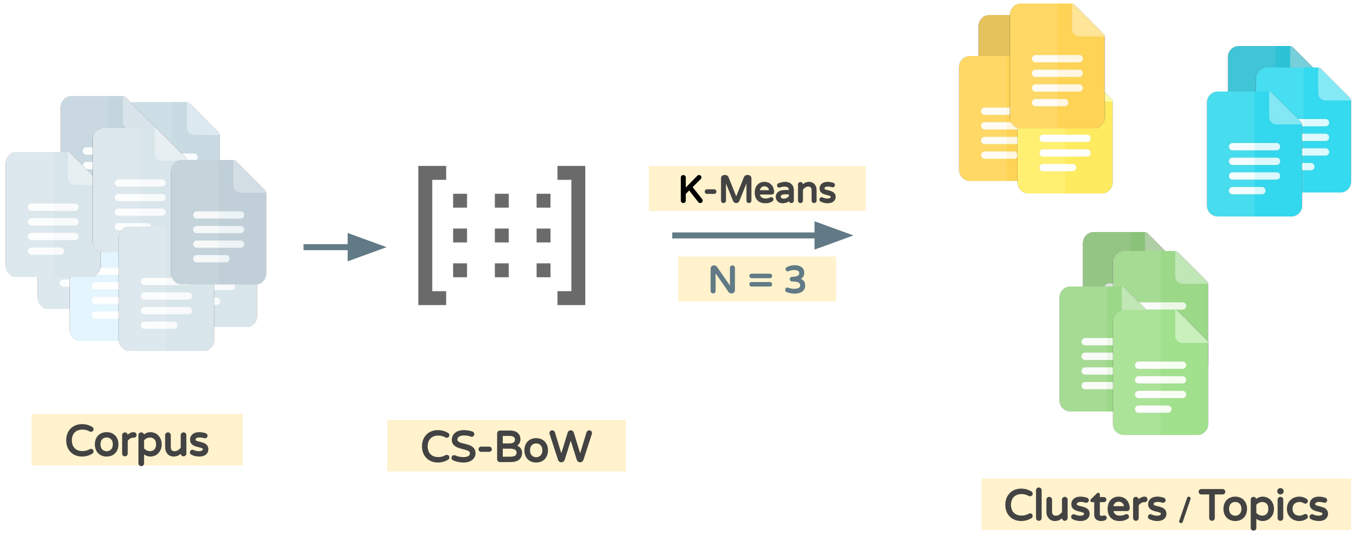
=

ball	1
championship	1
clown	0
friend	0
football	1
french	1
game	0
match	1
pain	0
peace	0
sport	1
team	1+1
telephone	0
war	0
win	1+1

CS-BoW

** for each word in the document, we generate a filtered subgraph*

2. CSTM



Evaluation

Datasets

- **BBC News:**
  A news dataset from BBC containing 2225 English news articles classified in 5 categories: “Politics", “Business", “Entertainment", “Sports" and “Tech”

- **AG News:**
  A news dataset containing 127600 news articles from various sources, fairly distributed among 4 categories: “World", “Sports", “Business" and “Sci/Tech"

- **20NewsGroup:**
  a collection of 18000 user-generated forum posts arranged into 20 groups seen as topics such as“Baseball", “Space", “Cryptography", and “Middle East".

- **AFP News:**
  a dataset containing 70K English news articles issued by the French News Agency, with top-level categories such as “Politics", “Art, Culture and Entertainment", “Environment". The label distribution is highly unbalanced.

Quantitative Analysis

Dataset	Model	V-Measure	WE-Coherence	NPMI
BBC	CSTM	**0.789**	**0.382**	-0.132
	K-Means	0.662	0.346	0.105
	LDA	0.729	0.359	0.122
	NMF	0.172	0.371	0.0225
AG News	CSTM	0.250	**0.387**	-0.0539
	K-Means	0.171	0.225	**0.027**
	LDA	**0.542**	0.214	0.001
	NMF	0.092	0.306	-0.0017
20NG	CSTM	0.403	0.303	-0.055
	K-Means	**0.433**	0.246	**0.127**
	LDA	0.403	**0.353**	0.031
	NMF	0.274	0.281	0.092
AFP	CSTM	0.431	0.296	-0.0459
	K-Means	**0.447**	**0.329**	**0.159**
	LDA	0.297	0.322	0.075
	NMF	0.409	0.308	0.127

Quantitative performance of CSTM and Baselines on 4 datasets.
Best result on each dataset-metric pair is highlighted in bold

Human evaluation

➜ Word Intrusion

e.g. game, stock, sport, football, rugby

> Intruder word is :
> **stock**

➜ Topic Labeling

e.g. medicine, illness, disease, medication, medical

> Corresponding label is :
> **Medicine**

➜ Topic Classification

e.g. “Deutsche Bank reports first annual profit in four years”

> Corresponding topic is :
> **business, commerce, value, market, finance**

Quantitative Analysis

Model	Word Intrusion	Topic Labeling	Topic Classification
CSTM	**83.3%**	**84.6%**	**27.5%**
K-Means	33.3%	81.7%	19.5%
LDA	29.2%	52.9%	13.3%

Scores percentage (w.r.t the maximum obtainable) across datasets for CSTM, K-Means and LDA

Future Work

- Try other BoW/TF-iDF variants for CS-BoW
- Use other clustering methods
  (even topic models!)
- Experiment with other CS Knowledge Graphs
- Impact of number of topics/hyperparameters
- Towards topic labeling

Thank you

Any questions?

K-CAP 2021: https://doi.org/10.1145/3460210.3493586

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Code & Evaluation: https://github.com/D2KLab/CSTM