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# Unsupervised Learning of News Articles using a Custom Topic Modelling Method

BrainStation Capstone Project  
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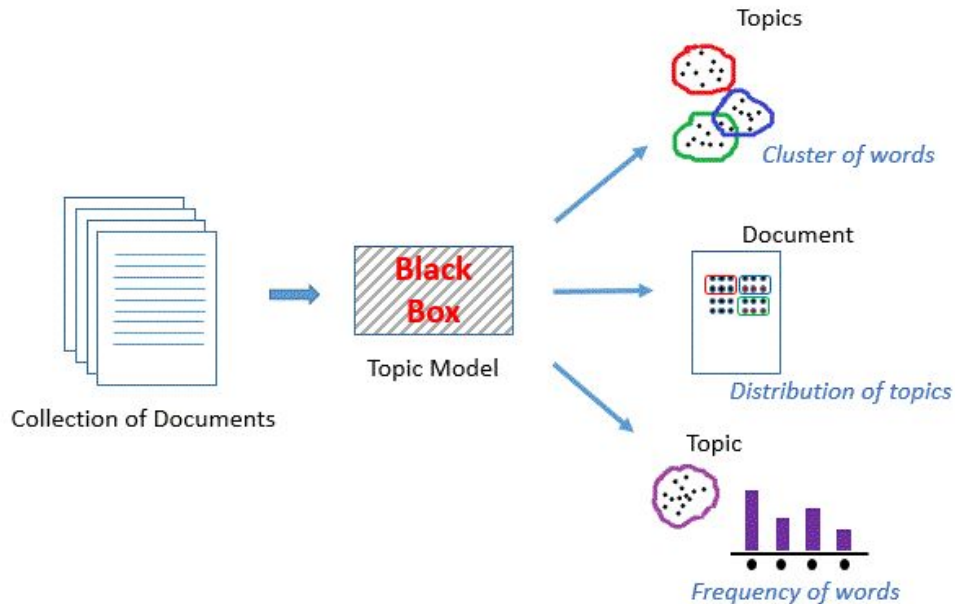
# Problem Statement

Using **Unsupervised Natural Language Processing**, how might I conduct **topic modelling** on an article database from a news network to optimize current classification?

# Background

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# What is Topic Modelling?



# Context

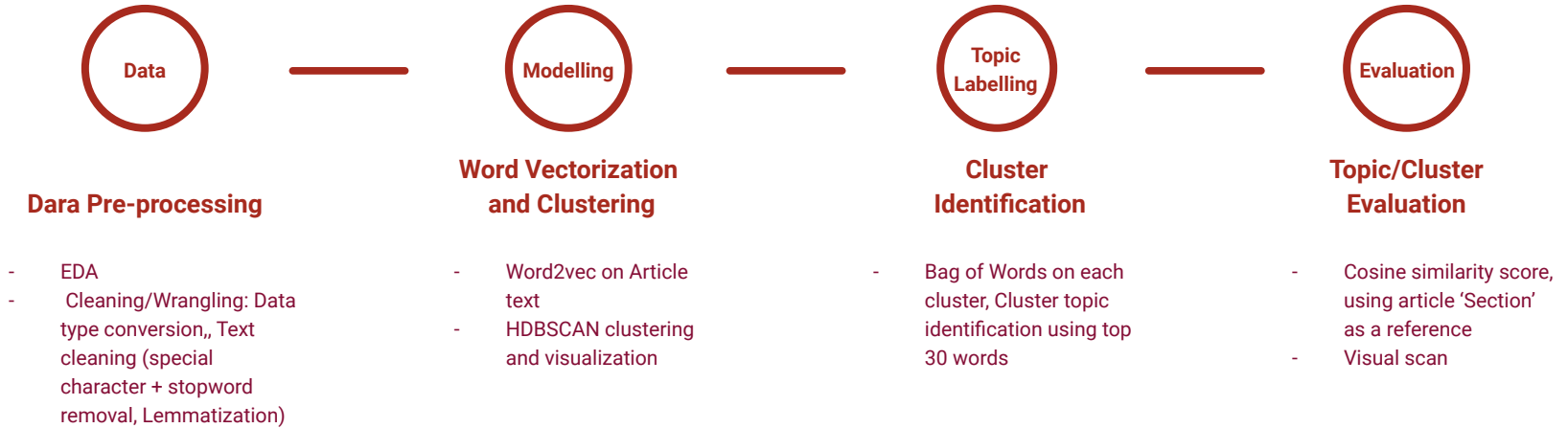
In the age where many read the news digitally, **topic modelling** can help a business:

- Inform website hierarchy, increasing user experience for site visitors
- Determine the most relevant tags to use, improving SEO





# Project Workflow





# Data Collection

- Dataset from Kaggle
- Articles from CNN website from 2011-2022:
- 38,000 rows, 11 columns:
  - Author
  - Date Published
  - Category
  - Section
  - Headline, Description, Keywords, Article Text

# Results

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# HDBSCAN Cluster Results

- 60 valid clusters (excluding noise cluster)
  - 28.2% of the data in the noise cluster
  - Second largest cluster slightly smaller at 27%
- Validity score after running pipeline= 37.8%





Cluster  
Identification

# Cluster Identification - Labelling

cluster	top30words
-1	[best, world, new, state, president, country, 2012, woman, day, coronavirus, government, like, trump, could, russia, according, right, many, police, family, ukraine, get, life, match, video, child, home, group, may, city]
0	[ukraine, crisis, 168, ukrainian, march, prorussian, may, april, russian, building, slovyansk, donetsk, 132, guard, police, military, near, stand, soldier, crimea, kiev, outside, activist, armed, force, front, regional, government, protester, troop]
1	[golf, open, best, wood, round, shot, master, ryder, major, hole, pga, cup, world, win, tour, tiger, championship, course, player, back, 2012, day, play, second, mcilroy, tournament, video, must, british, final]
2	[open, tennis, match, slam, grand, set, final, win, world, williams, djokovic, player, title, federer, nadal, wimbledon, french, australian, must, video, court, champion, play, tournament, murray, second, serena, game, back, round]
3	[news, hacking, murdoch, phone, police, world, british, newspaper, former, brook, inquiry, editor, corp, must, international, video, scandal, medium, journalist, tabloid, public, investigation, minister, sun, cameron, voice, rupert, charge, uk, mail]
4	[pope, francis, vatican, church, catholic, abuse, cardinal, benedict, priest, new, bishop, sexual, child, must, world, st, report, john, video, peter, rome, visit, 44, day, victim, xvi, holy, mass, papal, meeting]
5	[race, f1, driver, team, formula, car, hamilton, grand, season, world, prix, champion, vettel, win, title, second, championship, new, racing, sport, bull, must, red, mercedes, video, ferrari, lewis, point, back, track]
6	[world, team, game, player, league, football, club, cup, sport, win, season, champion, goal, new, day, match, final, fan, like, second, video, best, must, city, back, 10, woman, olympic, home, play]



Cluster 0 : 'ukraine, crisis'

Cluster 1: 'golf'

Cluster 2: 'tennis'

Cluster 3: 'journalism, scandal'

Cluster 4: 'religion'

Cluster 5: 'racing'

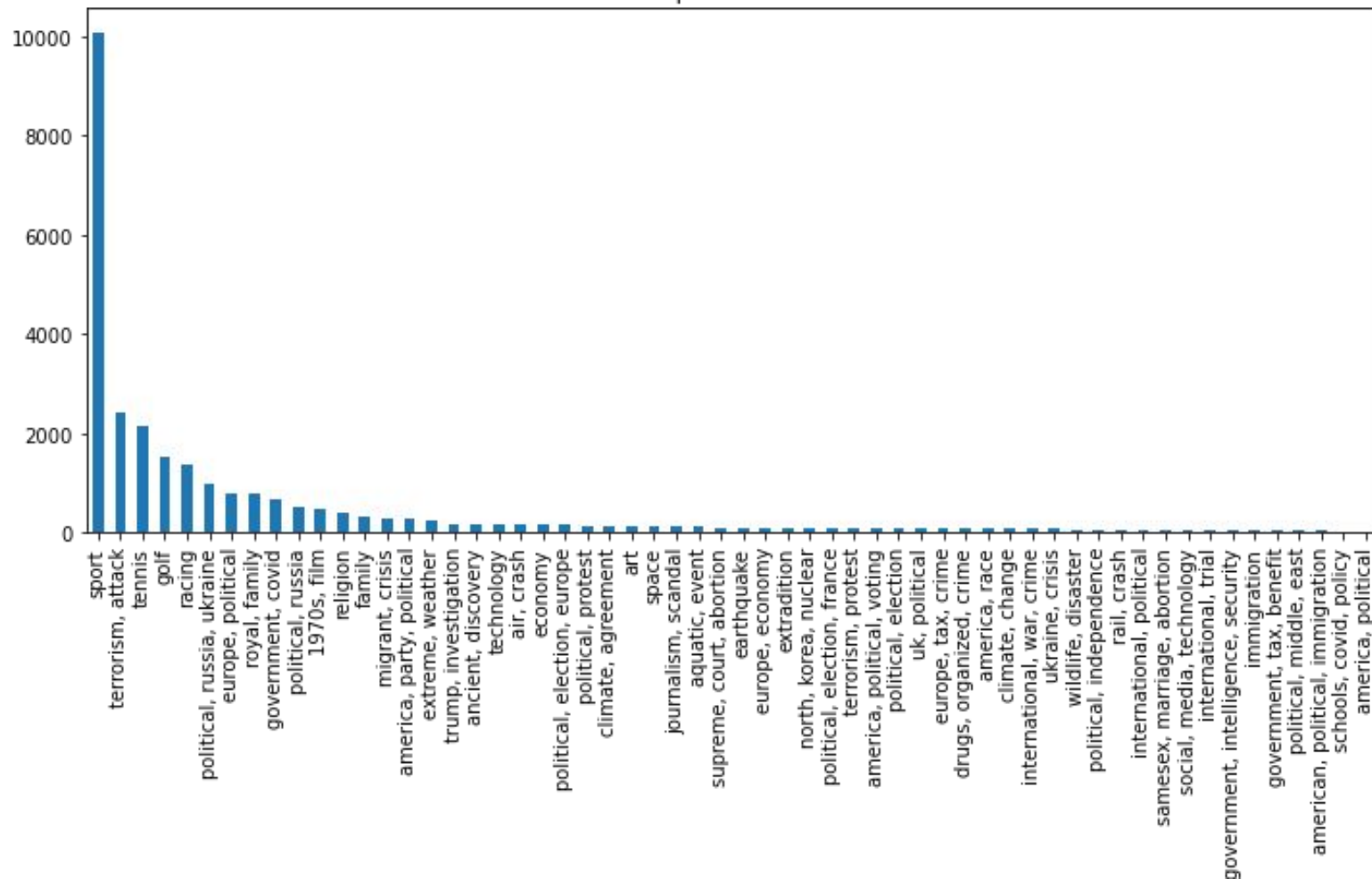
Cluster 6: 'sport'

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# Histogram of Topic Clusters Determined by My Model



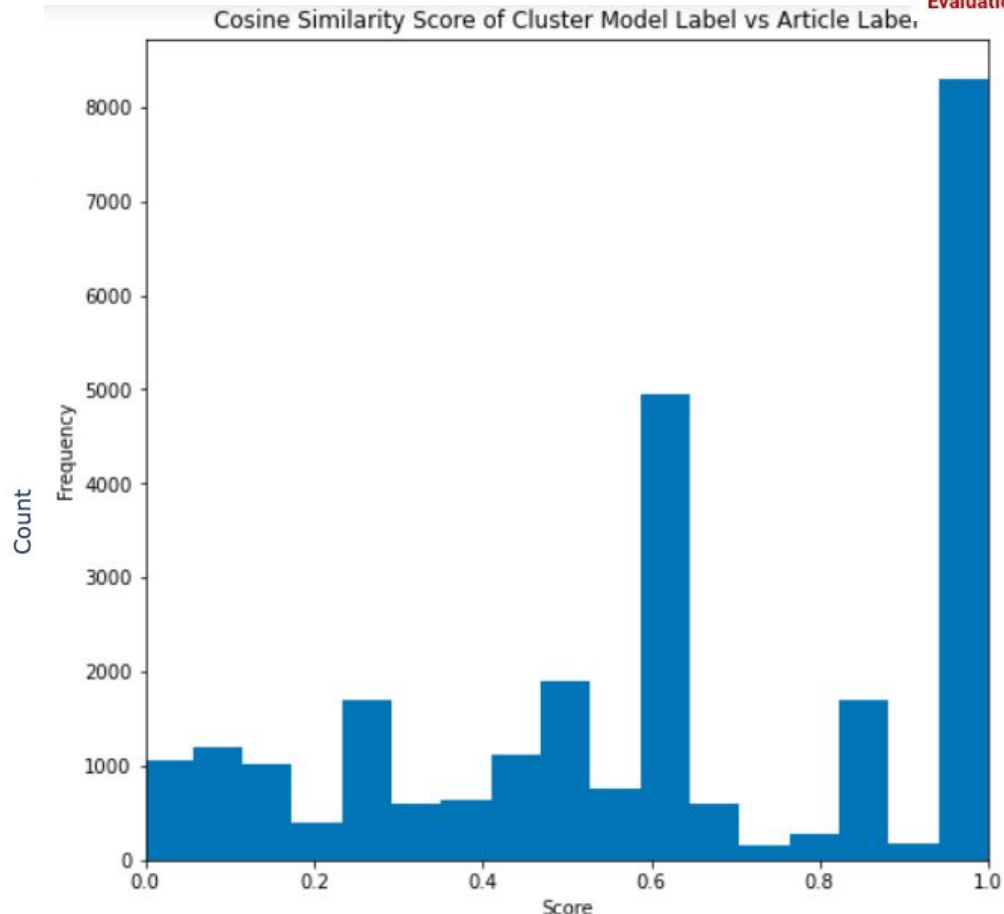
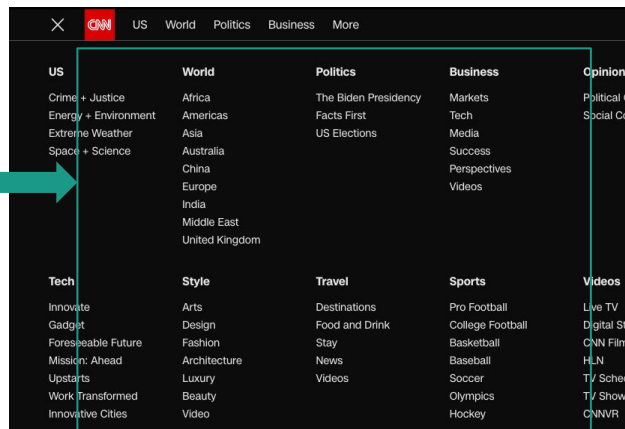
Topic/Cluster  
Evaluation



# Cluster Performance - Cosine Similarity Score of My Label vs CNN Section Label

- 100% similarity score for 30.9% of the documents!
- Average score was 62.7%
- Over  $\frac{2}{3}$  of the articles had a score higher than 50%
- 50th percentile at a score of 64%, 25th percentile at a score of 40% or below

CNN  
section  
label



# Cluster Model / Topic Performance - Visual Scan

Most cluster labels captured the topic quite well and in many cases had more granularity than Section  
This also revealed some weaknesses in the Word2vec vectors used to determine similarity score

Section label				My model label			
Year published	Month_year published	Category	Section	Article text	cluster ID	cluster category	cosine_similarity_score_rounded
33169	2020	2020-08	sport	(CNN)Serena Williams came back from the brink...	2	tennis	0.50
29491	2019	2019-06	news	Moscow (CNN)Russian President Vladimir Putin h...	33	political, russia	0.50
33224	2020	2020-08	news	(CNN)A light aircraft overloaded with cocaine...	41	drugs, organized, crime	0.17
25992	2018	2018-05	news	Rome (CNN)A victim of clerical sexual abuse ha...	4	religion	0.15
5513	2019	2019-08	news	(CNN)After months of record temperatures, sci...	28	extreme, weather	0.13
27619	2018	2018-11	news	(CNN)Nervous fliers, stop reading now.A Japan...	23	air, crash	0.12
34491	2021	2021-02	news	(CNN)Prince Philip has spent a second night i...	7	royal, family	0.11
5529	2016	2016-01	news	(CNN)The Rev. Martin Luther King Jr. was a Re...	55	america, race	0.11

# Cluster Model / Topic Performance - Visual Scan

Other cluster labels (a smaller amount) did not seem the most accurate

Section label					My model label			
	Year published	Month_year published	Category	Section	Article text	cluster ID	cluster category	cosine_similarity_score_rounded
10188	2016	2016-08	politics	politics	(CNN)Filmmaker Spike Lee said Monday Donald T...	6	sport	0.26
26600	2018	2018-07	news	europe	Rome (CNN)George Clooney has been released fro...	48	terrorism, attack	0.29
30809	2019	2019-10	sport	sport	(CNN)The New Orleans Saints got some unexpect...	4	religion	0.20

# Next Steps

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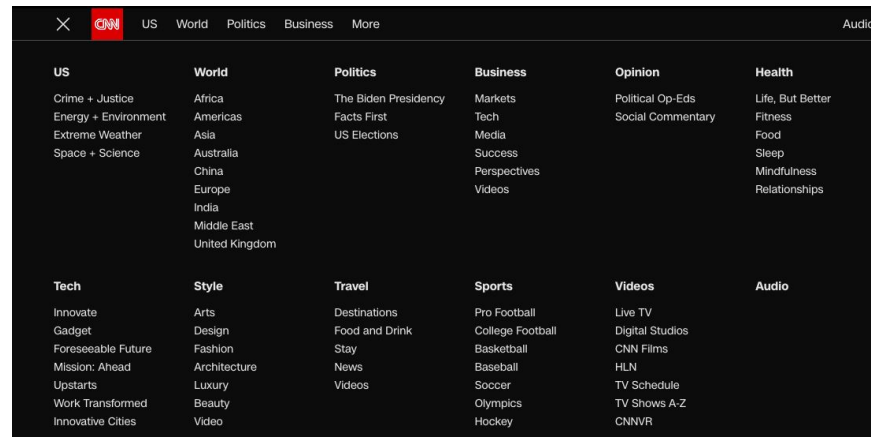
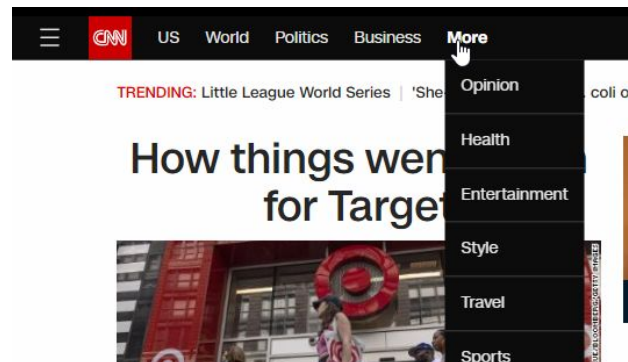
# Model Improvement

- **Word model:**  
There may be advantages in exploring another word model, such as BERT (which takes context into account)
- **Clustering model:**  
Find ideal balance between a high validity score for HDBSCAN model, smaller noise cluster, and cluster number



# Practical Applications

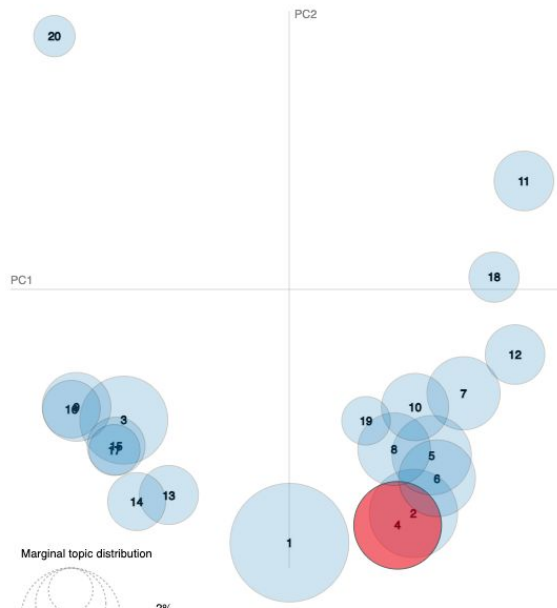
- Topics can be added as **tags** to current articles; CNN appears to not use meta tags, which will improve SEO
- Topics that were more granular than the current CNN section label can be added to the site **online navigation**



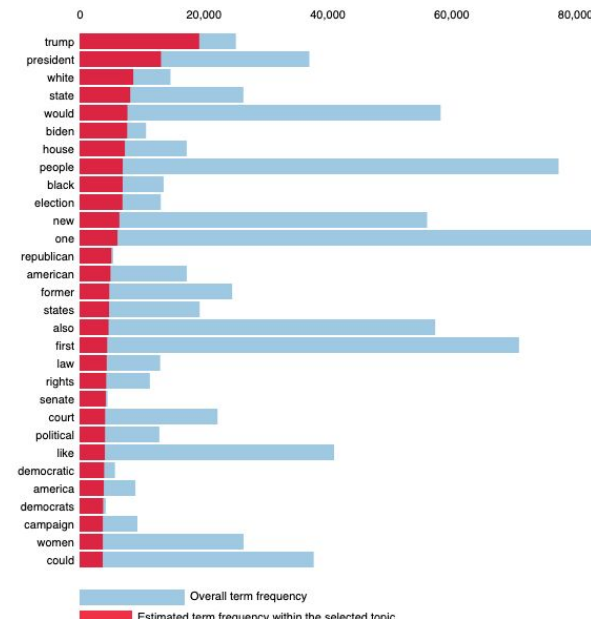
# Future Work

Carry out other common topic modelling methods (i.e. LDA) and compare its performance/findings to my model

Intertopic Distance Map (via multidimensional scaling)



Top-30 Most Relevant Terms for Topic 4 (7.8% of tokens)



**The end.  
Thank you!**

