

# THIS ARTICLE IS MADE FOR YOU

## Or how to optimize newspaper article recommendations

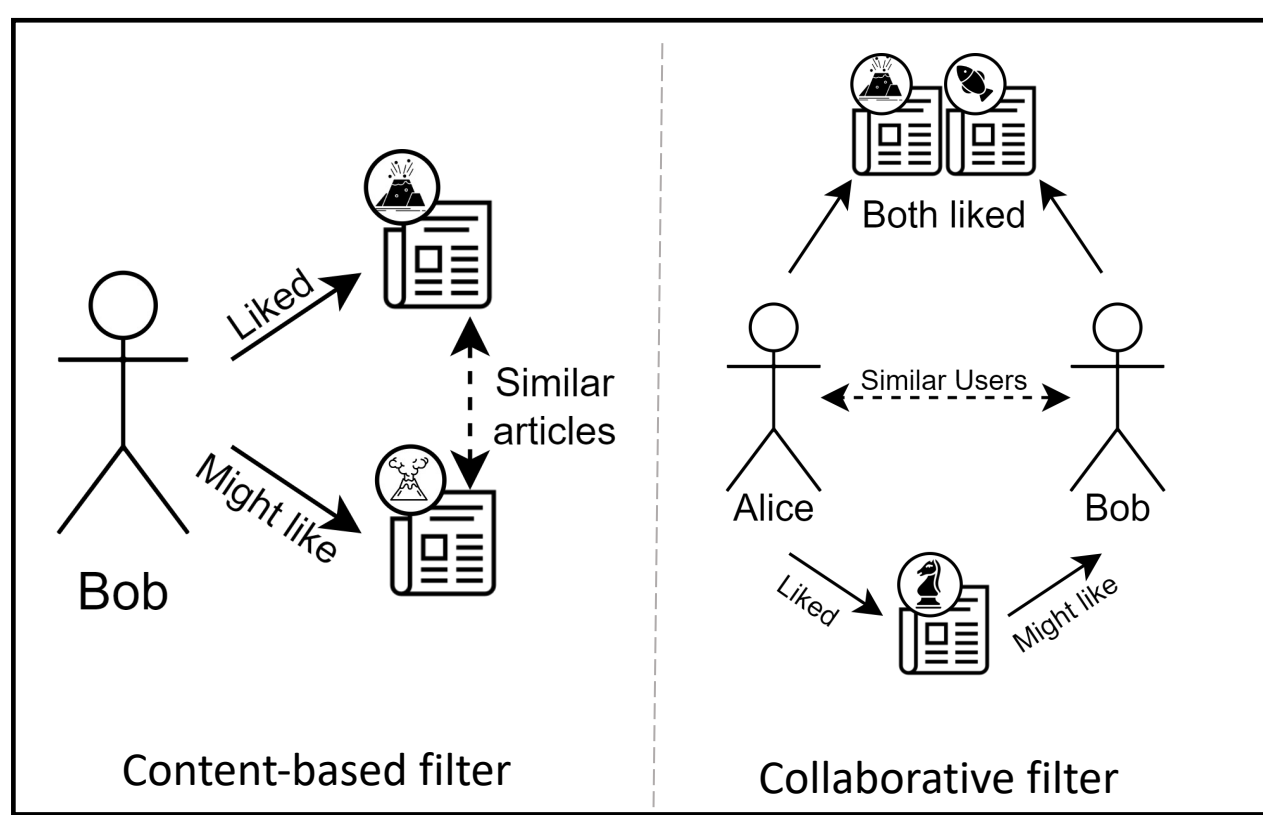
Arthur Gallois — Nathan Chalumeau — Ali Ramlaoui — Dimitri Martin —

**N**ews has become easily and massively accessible since the 1990s, thanks to the Internet. Collaborative recommendation filters, used by social media platform, rely on mass interactions [1]. These filters face challenges such as data volume, computational resources, and filter bubbles [2]. This paper develops new content-based recommendation filters using article writing style.

### Recommendation Methods

**Content-based:** rely on topic similarities between articles

**Collaborative:** uses user preferences similarities to suggest new articles

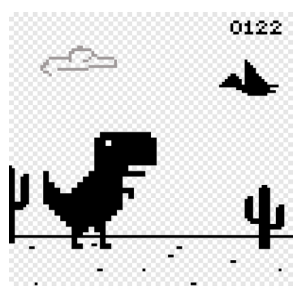


Collaborative vs Content-based filters

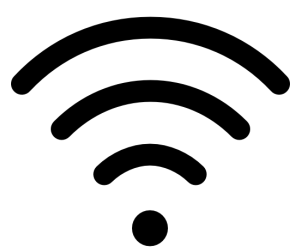
**Other** useable data:

Geographic, recently visited shops (google maps), internet search...

### Evaluation Methods



**Offline:** fixed dataset that includes user feedback without real-time update



**Online:** real-time interaction with users to assess models.



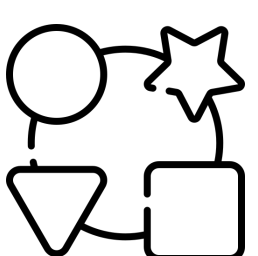
**Qualitative** method tries and focuses on new criteria:



Serendipity



Filter bubble



Diversity



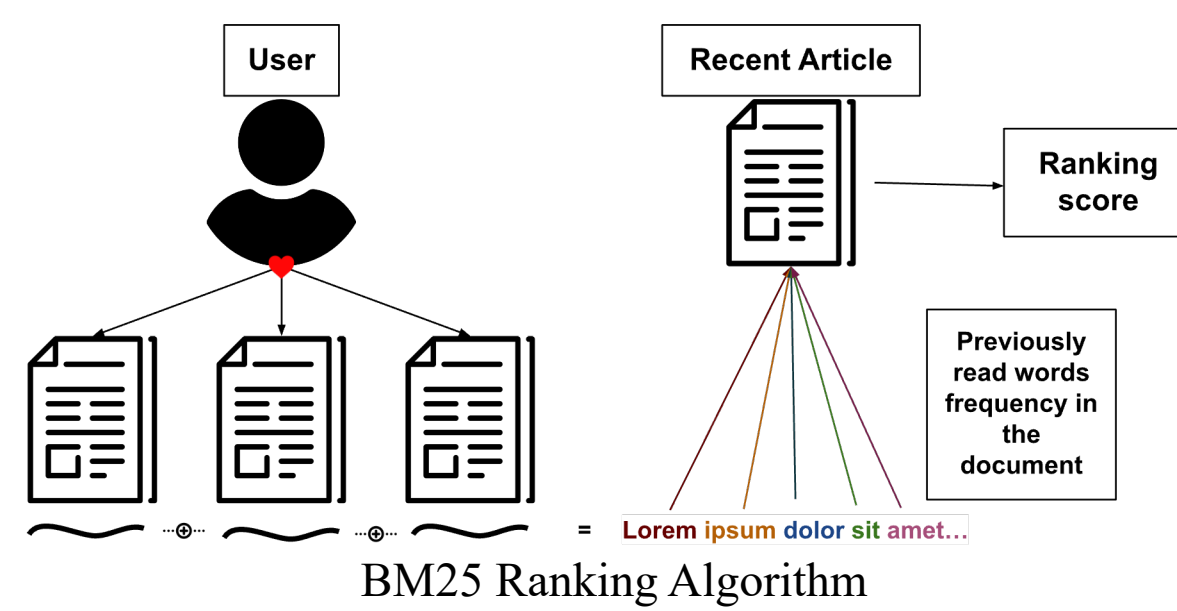
Novelty

N.B. : **Serendipity** = New + Surprising

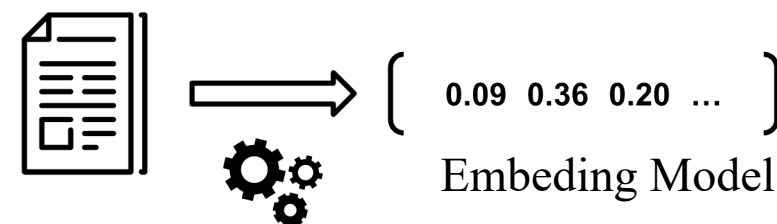
**Filter bubble:** Not a criterion but situation the algorithm should avoid

### Content-Based Algorithms

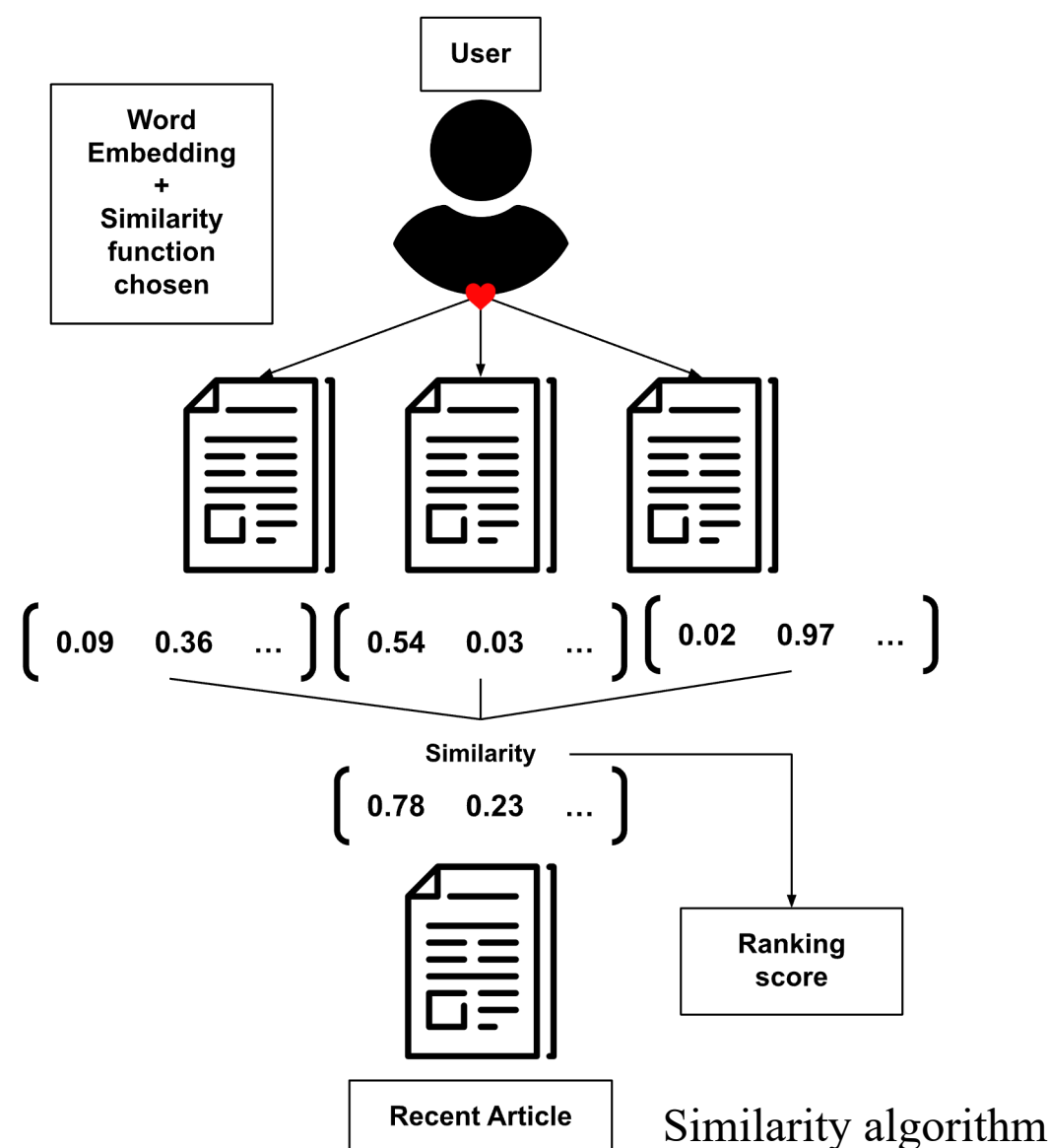
**BM25:** Widely used document similarity scoring algorithm based on word frequency



Word embedding techniques compute ranking scores using a similarity function.

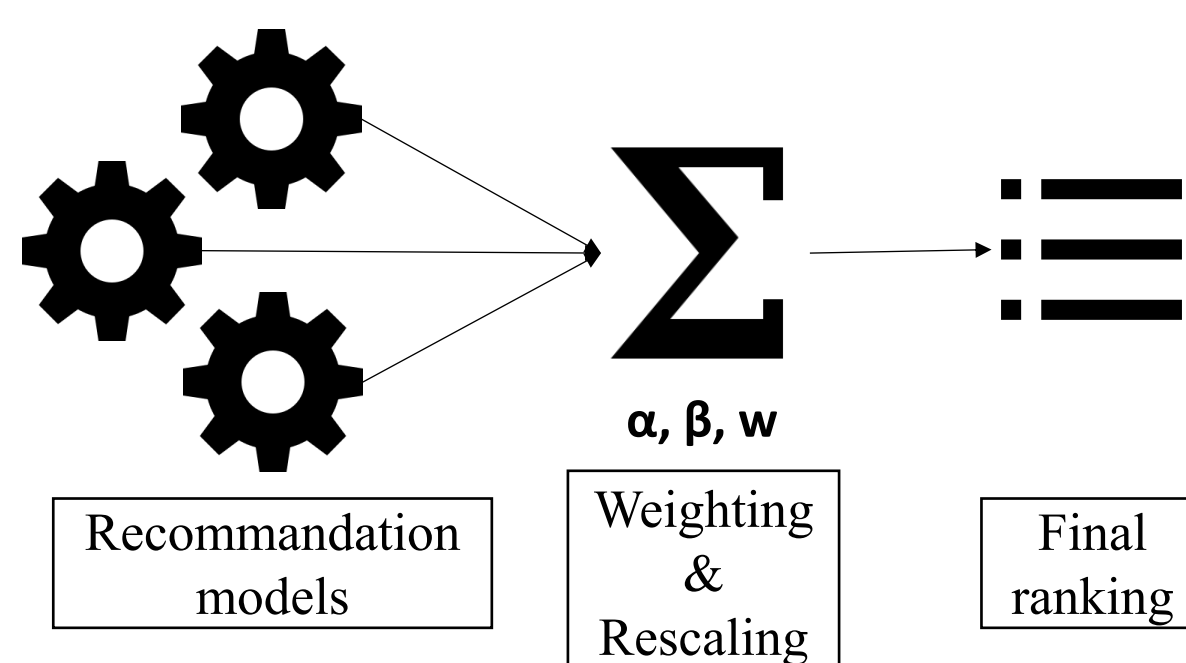


**Pertinent** word embedding models range from semantic models to style representation models.



### Combining Rankings

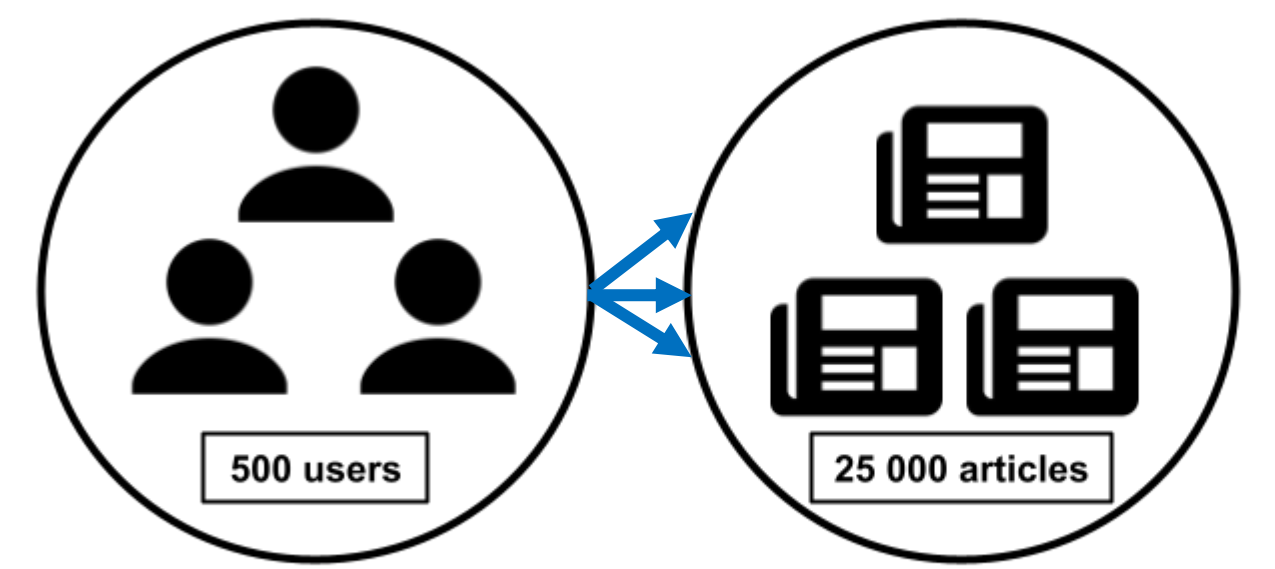
**Reswhy (Rescaled and Weighted Hybridization):** Models combined to extract information from all.



**Reswhy** is interesting on a combination of semantic model (**BM25**) and style-based model (**DBert-ft**).

### Training Dataset

The dataset we use is made of **Twitter** users and articles they shared.



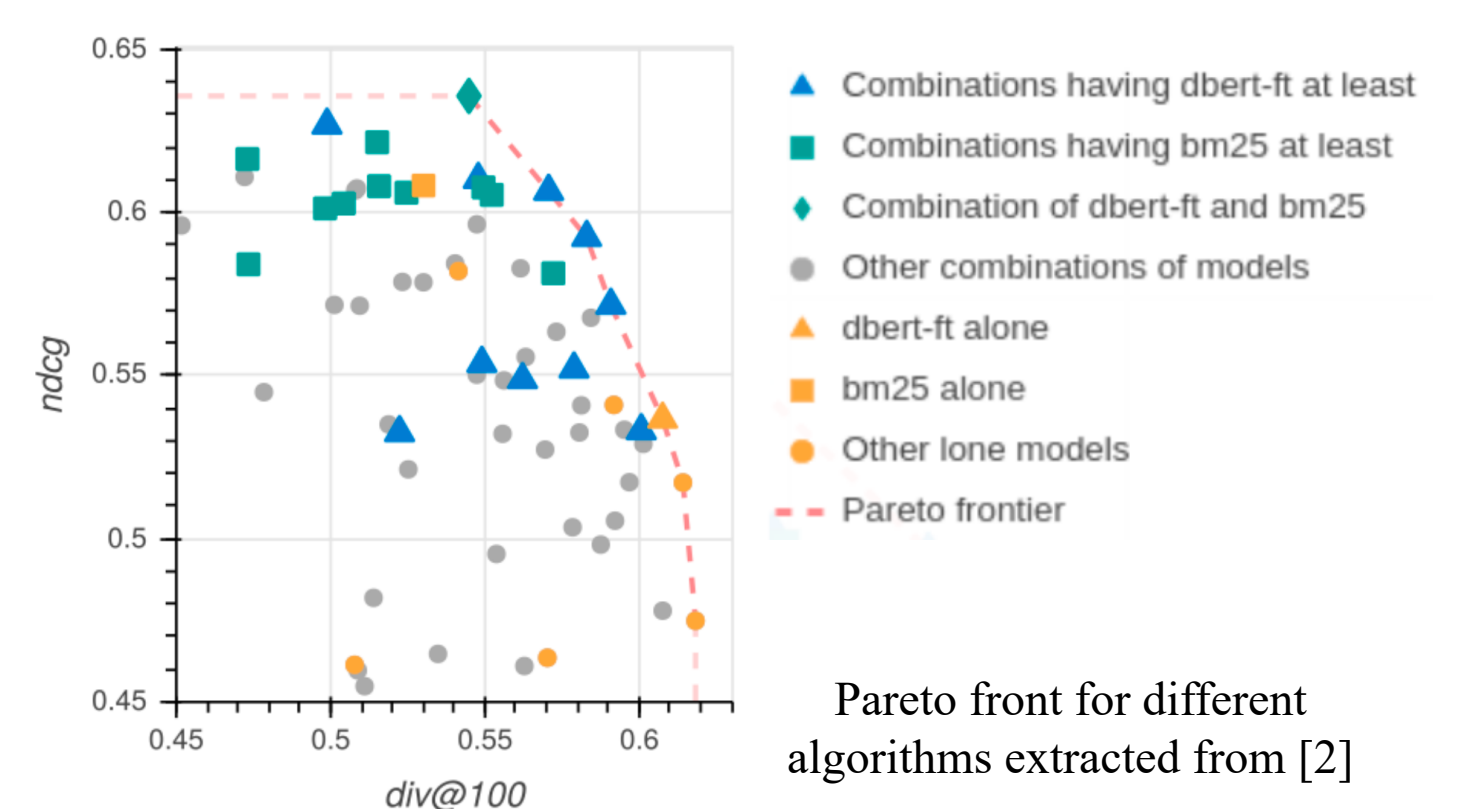
### Results

|          | nDCG | MRR  |
|----------|------|------|
| BM25     | 0.45 | 0.27 |
| DBert-ft | 0.53 | 0.46 |
| Reswhy   | 0.55 | 0.45 |

Results obtained to validate [2]

**nDCG:** Precision score considering item positions with decreasing weights

**MRR:** Score indicating how close the first relevant items in rankings are to the first position



**Pareto fronts** are used to identify the best algorithms that favor multiple criteria simultaneously.

**Style-based** models give complementary information to **semantic** models and are interesting to explore with multi-modal data (video, images, text...)

### References

- [1] Claypool, M. (1999) « Combining Content-Based and Collaborative Filters in an Online Newspaper. SIGIR'99 Workshop on Recommender Systems : Algorithms and Evaluation »
- [2] Hay, J. (2021) « Apprentissage de la représentation du style écrit, application à la recommandation d'articles d'actualité »
- [3] Burke, R. (2007) « Hybrid Web Recommender Systems ».