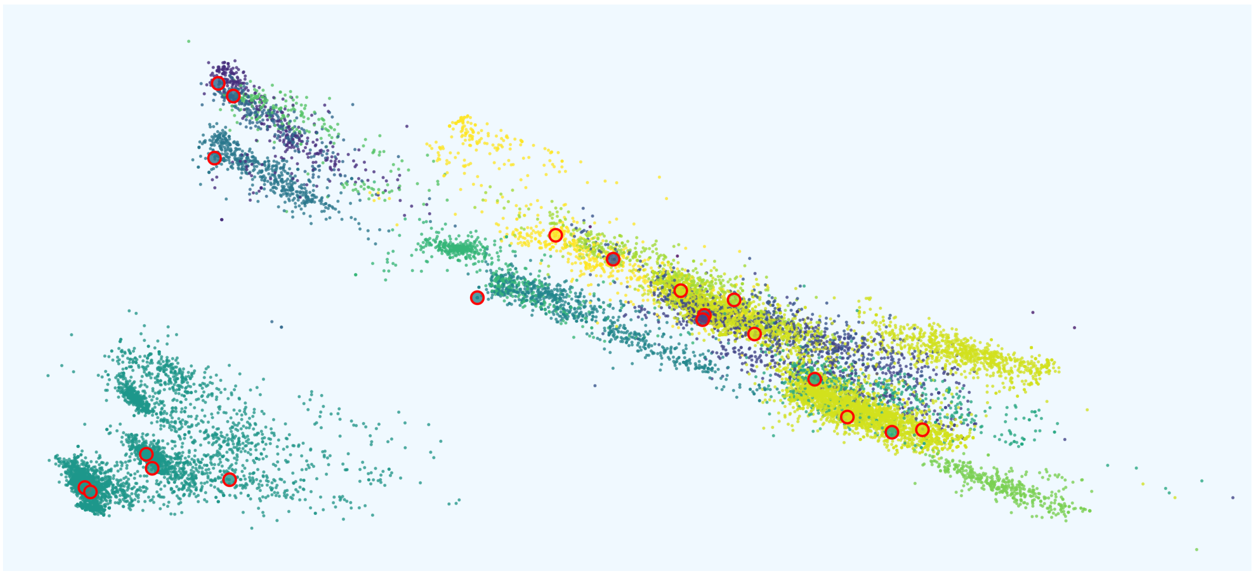
This article is a draft, awaiting review for publication in Distill



Making Recommendation Systems More Transparent to the Lay User

A project for the course *Interactive Machine Learning*, tought by Dr. Menna Elassady in Spring 2022

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Abstract

Social media and online platforms have a huge impact on what people get exposed to, mainly through recommendations. It is therefore primordial to make the recommendation process as much transparent as possible. In this project, we built a news feed powered by more and less interpretable recommendation systems, along with a dashboard to interact with them.

Introduction

According to the 2021 survey on news consumption across social media, roughly half of US adults report getting news from social media at least sometimes [1]. Given that recommendation systems determine what news articles users get exposed to and read, it is important for everybody to understand how they work. To facilitate the understanding of these algorithms, we implemented three recommendation systems, one of which being designed to be highly interpretable and customizable. Some summary statistics and visualizations are displayed along the news feed, so as for the user to get a better grasp of what the models recommended. This interactivity is provided through a web interface developed for this project.

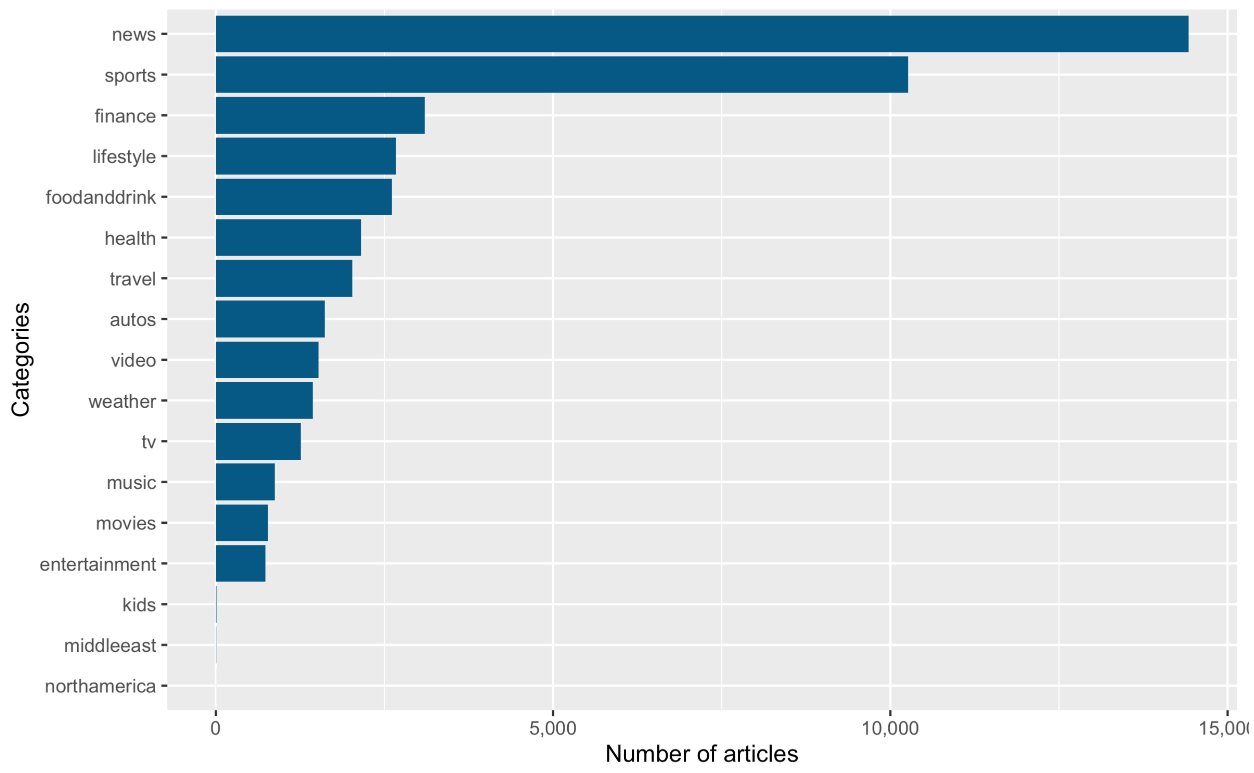
Dataset

We used the Microsoft News Dataset (MiND) [2], a large-scale dataset for news recommendation research, collected from anonymized behavior logs of the Microsoft News website. For the purpose of our project, we used the demo flavor of the dataset – a smaller version of the original one. It consists of two main datasets: one on news articles and one on user behaviors, as detailed below.

	News dataset	**User dataset**
Training dataset	26,740 records	22,034 records
Validation dataset	18,723 records	7,538 records

News dataset

Each row corresponds to a news article, and contains its title and abstract, along with the url to fetch it online. Some metadata on the news article is also provided in the dataset: the category and subcategory of the news tackled in the article, as well as the list of entities extracted from its title and from its abstract, using the Wikidata knowledge graph[1].



Number of articles per category in the news dataset

Below, you can see an example of subcategories for the category "video":

Category	Sub-categories
video	animals
	lifestyle
	news
	popculture
	science
	viral
	video

User dataset

Each row corresponds to an “impression”, that is to say a set of recommended news displayed to a user, along with the news click history of the user, and a label to know which impressed news article was ultimately clicked on. There is also the date and time of the impression. Note that some users appear several times in the dataset, as each row corresponds to a new impression (but not necessarily to a new user).

Embedding datasets

Along with the two main datasets, the MiND also contains pre-generated, 100-dimensional embeddings of the extracted Wikidata entities, and of their relationships to one another.

Preprocessing

As will be discussed in the model section, we needed to embed news and users in order to make recommendations. In the following subsections, we will discuss how we proceeded.

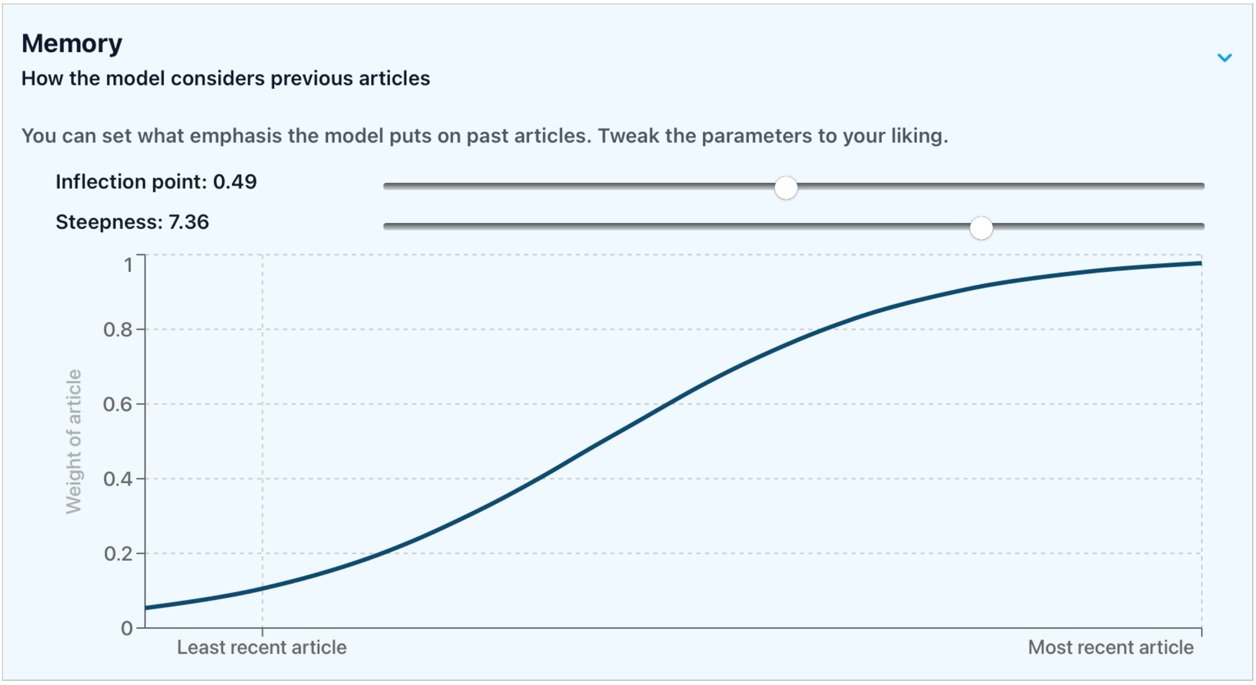
News dataset

To create news embeddings, we relied on the entity embeddings provided in the MiND. After dropping the articles without any extracted entity, we embedded news articles as the average of the embeddings of all the entities extracted from their title and/or abstract.

Additionally, we wanted to add the metadata on the news (sub)category. However, merely label-encoding them would only add one dimension to the hundred already existing, and the (sub)category information would likely be overlooked by the models. Thus, we decided to encode them as the average embedding of all the news articles from a given (sub)category, and to concatenate them to the existing embeddings, leading to 300-dimensional news embeddings.

User dataset

We proceeded likewise to create user embeddings, using the average of the embeddings of all the news articles in their history.


Memory
How the model considers previous articles

You can set what emphasis the model puts on past articles. Tweak the parameters to your liking.

Inflection point: 0.49
Steepness: 7.36

Example logistic curve used to assign different weights to past articles

However, we also implemented a “memory” behavior: that is, most recent articles in the history are assigned larger weights than news articles read a long time ago. This behavior can be toggled by the user and takes the form of a logistic curve.

Models

To highlight to the user the differences between recommendation systems, we implemented three different models that make recommendations.

Random model

This baseline model generates random embeddings, and makes random recommendations. It does not take into account history and does not allow for hyperparameter customization.

Black box model

The black box model we implemented is a Long- and Short-Term User Representations (LSTUR) [3] model, a neural network using news and user encoders to learn both users' long-term preferences and their short-term interests. It was implemented using the microsoft/recommenders Python package. This model was selected as it is deemed as state-of-the-art in the world of news recommendations, and as its inner mechanisms are fairly intricate - especially for the lay user - hence the "black box" alias.

White box model

The white box model is the core of the project. It is a homemade, interpretable and customizable recommendation system. More specifically, it makes recommendations according to a mix of three methods the user can choose the proportions of:

- **Content-based recommendation**: Recommending news articles most similar to the articles already read by the current user. Concretely, news articles are ranked by the (cosine) similarity of their embedding to the current user's.

- **Popularity-based recommendation**: Recommending news articles most popular among other users. Concretely, news articles are ranked by the number of times they were clicked on by users, and by the ratio of the number of clicks on over the number of impressions.

- **Collaborative filtering recommendation**: Recommending news articles that were read by users most similar to the current user. Concretely, users are assigned weights proportional to the (cosine) similarity of their embedding to the current user. Then, articles are ranked by the sum of the scores of all the users who have read them.

Each method yields a score for every single news article. In the dashboard we developed, the user can choose the weight of each method in the news feed: in practice, the final score of each news articles is computed as the weighted sum of the scores from the three methods hereinabove.

On top of this, we let the user choose the weights assigned to more/less recent articles in the history, by way of a customizable logistic curve.

However, such recommendation system, though pretty simple and interpretable, is still very much subject to popularity bias. This results in more popular articles being recommended even more, by the popularity-based and collaborative filtering methods. Additionally, the system also suffers from the echo chamber effect: being “locked” in one single category by recommendation systems, which recommend the same category over and over to a user. This effect is due to the (over)use of similarity-based recommendations, as in white box’s content-based and collaborative filtering recommendation methods.

To temper such effects, which are intrinsic to all the standard recommendation system, we developed features to let the user choose if they want to add the following side objectives, and to what extent:

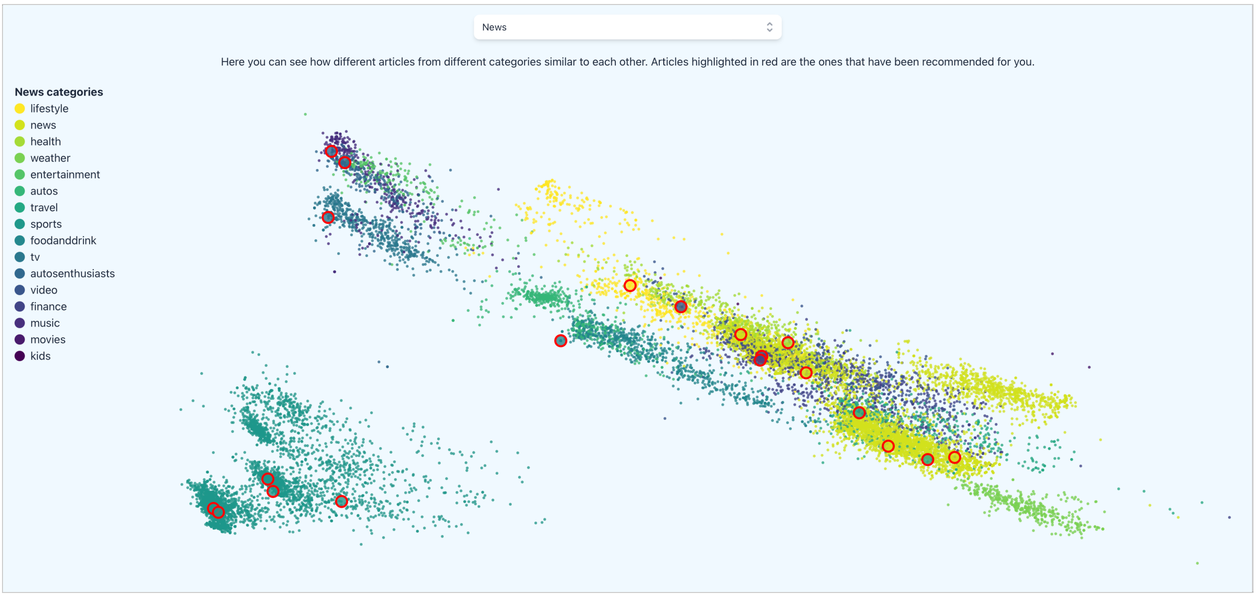
- **Diversity:** Constraining the model to recommend news articles from different news categories. Concretely, after each draw, the probability to draw again an article from the same category as the one just drawn, decreases by the percentage chosen.

- **Exploration:** Allowing the model to draw news articles with lower scores as well. Concretely, probability weights used to draw the news articles are calculated using the logistic function - whose hyperparameters depend on the percentage chosen - on their scores.

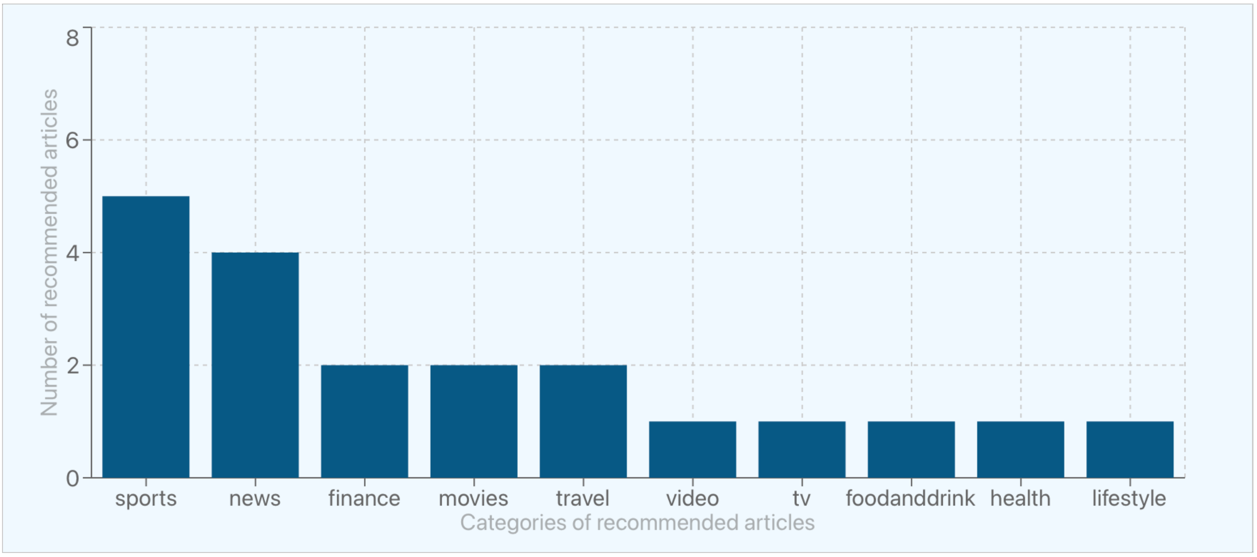
- **Surprise:** Requiring some random news articles among the recommendations. Concretely, the chosen percentage of the recommendations are drawn at random, and placed at random positions.

Visualization

We used Principal Component Analysis [4] to reduce news and user embeddings into two-dimensional embeddings, so as to graphically plot them. News embeddings are colored according to their category (in an arbitrary order). In the news scatter plot, we highlight the recommended news articles so as to get a qualitative sense of the diversity in the recommended news set.

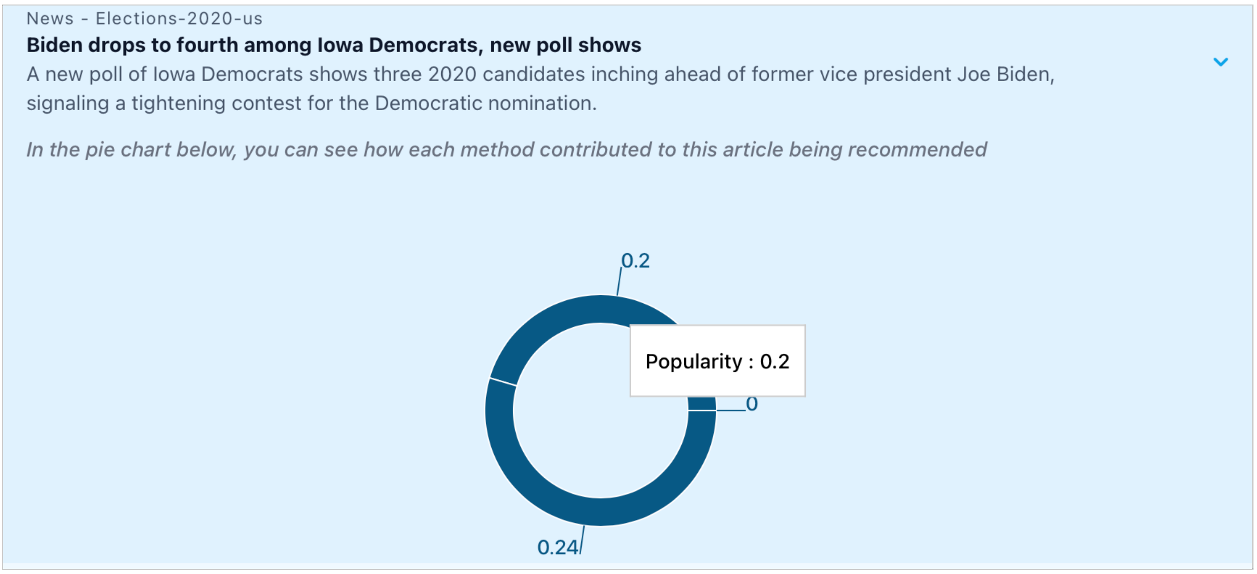


PCA reduction of news embeddings along with higlighted recommendations



Statistics for a given set of recommended articles

In addition to this, we provide a bar chart of the most represented categories in the recommended set. With this, the user can see the distribution across categories, of the news that got recommended to them. This visualization is useful to get a quick grasp of the diversity within the recommended set, and to compare different models and hyperparameter sets.



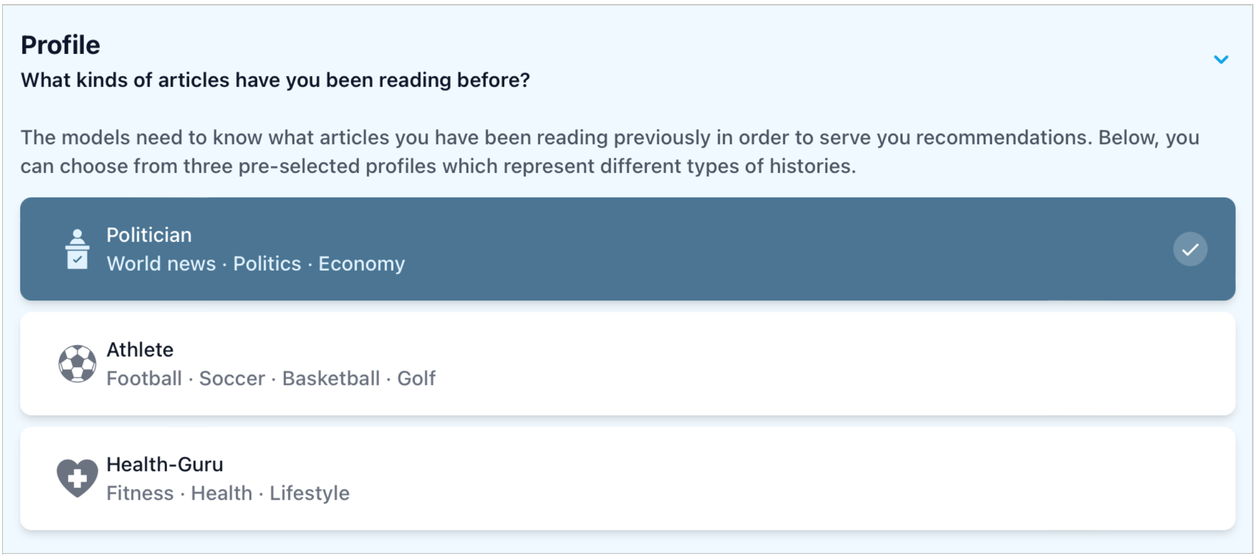
News - Elections-2020-us

Biden drops to fourth among Iowa Democrats, new poll shows

A new poll of Iowa Democrats shows three 2020 candidates inching ahead of former vice president Joe Biden, signaling a tightening contest for the Democratic nomination.

In the pie chart below, you can see how each method contributed to this article being recommended

Pie chart showing how much each method contributed to a recommendation



Profile

What kinds of articles have you been reading before?

The models need to know what articles you have been reading previously in order to serve you recommendations. Below, you can choose from three pre-selected profiles which represent different types of histories.

[✓ Politician
World news · Politics · Economy]

Athlete
Football · Soccer · Basketball · Golf

Health-Guru
Fitness · Health · Lifestyle

Profile selection in the web application

For interpretability purposes, we allow the user to see how much each method contributed in recommending a given article to them, in the form of a pie chart[2].

To make the overall demo easier, we created three profiles, each being defined by its favorite news subcategories:

- Athlete (football_nfl, basketball_nba, soccer)
- Health guru (fitness, healthyliving, weightloss)
- Politician (newsworld, newspolitics, financenews)

To build their histories, we drew at random a set of twenty articles from their favorite subcategories.

Conclusion

Above, we presented our implementation of an explainable recommendation system. However, there are many directions for further improvements.

- **Different embedding methods** - We used the embeddings provided by the MiND, and built news and users embeddings by averaging them. Using text embeddings (from news titles or abstract) and taking into account the date and time of the impressions may lead to better results.

- **Performance evaluation** - We did not directly evaluate the performance of each model, eg. how well the user would be expected to read the recommended articles. Indeed, the standard evaluation method for the MiND challenge does not reflect what we wanted to showcase in this project: more transparent, customizable, diverse recommendation systems. Another set of metrics, measuring how diverse a set of recommendation is, or how prone to the echo chamber effect a model is, would be a definite improvement for quantitative comparison of recommendation models.

- **Social media posts** - This dataset only includes news articles. Yet it would be very insightful to look at this project from a social media perspective, so as to model the variety of content people actually get exposed to on social media.

- **More interactive visualizations** - In this version of the dashboard, we for example do not allow for zooming into the visualization of the news and user embeddings, nor for hovering over specific articles to see information about them. While we try to provide a user journey through the dashboard, we could add a step-by-step introduction to all the components, for example using the intro.js package. Also, more visualizations could be displayed on the dashboard, for the lay user to better understand the mechanism of each recommendation method for example. All of this would improve the user experience.

Contributions

Florian Abeillon was responsible for the backend: he built the models, generated the embeddings, and set up the API.

Sverrir Arnórsson was responsible for the frontend: he designed the user experience, visualizations and general appearance of the dashboard.

Elisabeth Stockinger started out as a member of the team, but dropped out around easter. Her responsibility was to create a surrogate model for the black box model.

Footnotes

1. Collaborative, open-source knowledge database
2. Because of his French heritage, Florian prefers the designation of origin “camembert plot”

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