CAN RECOMMENDATION ALGORITHMS LEARN USERS POLITICAL ATTITUDES ?

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ABSTRACT

- Collaborative filtering by **matrix factorization** at the core of many algorithmic recommendation systems.
- Feed on past user->item interactions
- Represent users and item in a **latent vector space**

Our work :

- Train a recommendation system on *Twitter*
- Show : **latent features** -> contain information about **ideological position of users**

Keywords: Collaborative filtering, Explainability, Recommendation algorithms, Political attitudes.

DATASET

We work on a dataset extracted from the french twitter data.
Data structures :

- User-Item interaction matrix :
  - Users : Twitter users (29.373)
  - Items : Domain shared by twitter users (32.639)
  - Interactions : Number of times a user shared a specific domain (4.018.848)
- User's political attitudes on 5 different axes [1].

Data selection : We consider the followers of the French Members of Parliament (MPs), that follow at least 3 MPs, and have at least 25 followers. We then collected all the domains tweeted by those users. We finally consider only the users having shared at least 10 different domains, and the domain shared by at least 10 different users.

CONTEXT

- **State of art :** Recommendations of content on social medias are *statistically different* according to the **political attitudes** of the users.
- **Uncertainty :** Which **mechanisms** bring those differences ?
- **Proposition :** Highlight statistical relationships between the latent dimensions of some recommendation algorithm and the political attitudes
- **Future development : Explain** and analyse the statistical relationship

THE ALGORITHM

Collaborative filtering by non-negative matrix factorization : popularized by Koren et al. in 2009 [2]. We chose to use this algorithm for our proof of concept due to his **simplicity** and **explainability**.

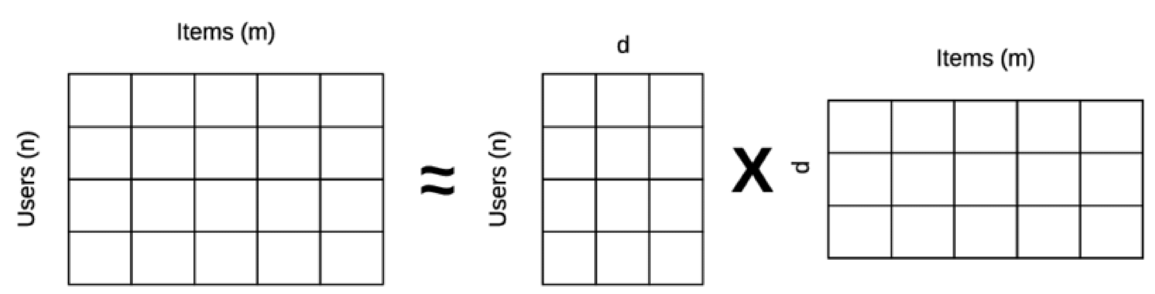
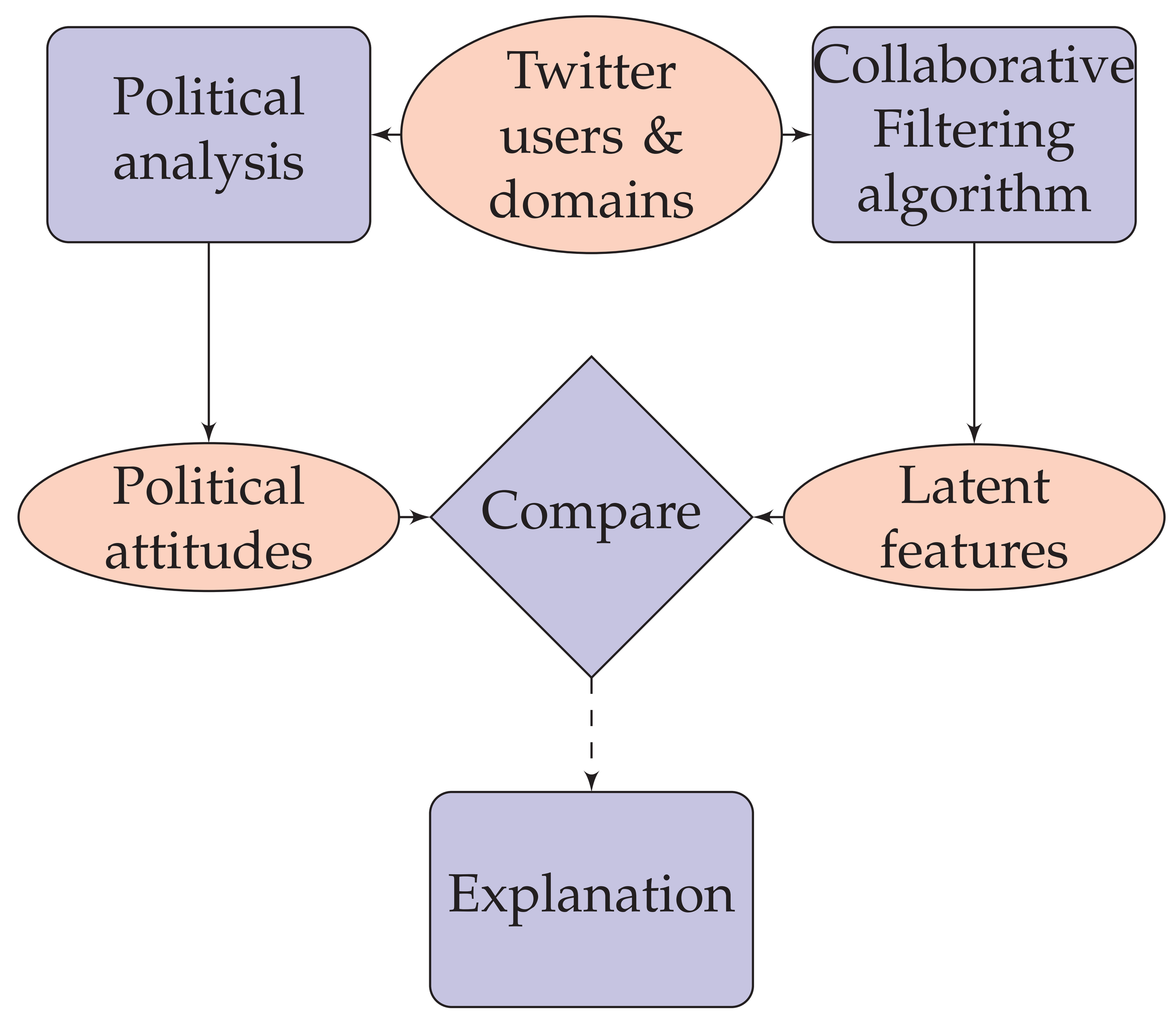


Figure 2: The sparse matrix of ratings is factorized into the 2 dense matrix associating to each user and item a latent vector into a d-dimensional space

New ratings estimation : scalar product between the user vector and the item vector.

METHODS

Overall method :



RESULTS 1

1. Studied the **correlations** between the latent features and the political dimensions.

Political axe	Pearson cor.	Spearman cor.
Left-Right	0.27	0.30
Local-Global	0.18	0.23
Immigration	0.16	0.21

Table 1: Here we see some of the best correlations between the political axis and the latent features (p-values are around 10^{-150})

- Correlation is higher for the users with **higher accuracy**.
- Correlation is higher for users with **higher latent features** (who has more impact on the loss function).

RESULTS 2

Possible to *predict* political attitude of users *from* latent features *using* simple linear regression model:

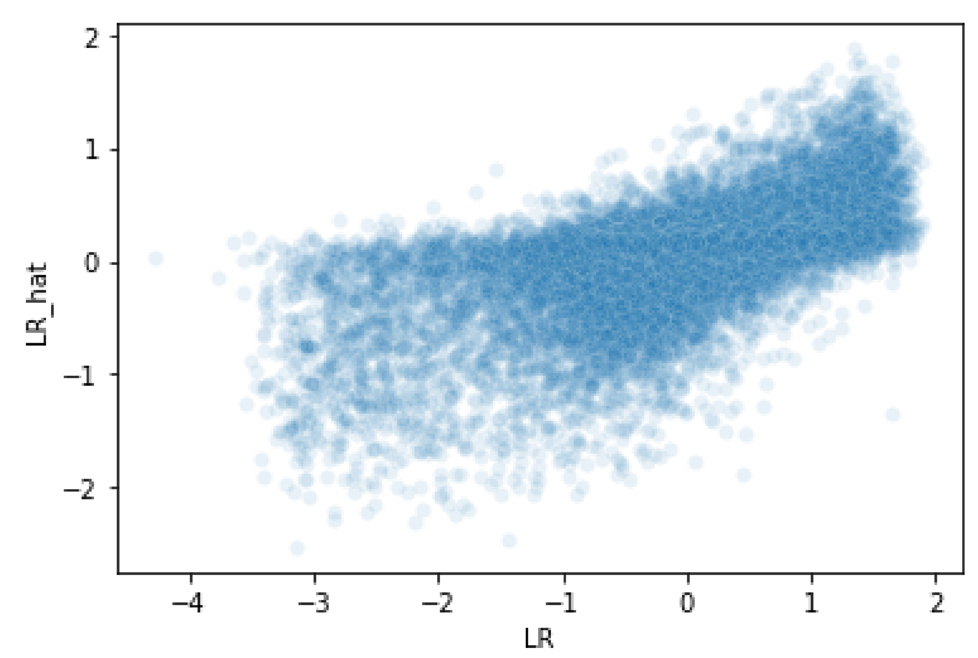


Figure 1: Plotted : **predicted** left-right (LR_hat) and **real** left-right attitude (LR). Correlation: 0.62, MSError: 0.65.

Conclusion :

- Shared links contain information about users' political attitudes.
- Non-negative Matrix Factorization utilize this information.
- Only part of this information is explainable by linear models
- This information impact the recommendations

Limits and opportunities :

- Observed only on specific collaborative filtering models
- Depend on pre-processing operations

REFERENCES

[1] Pedro Ramaciotti Morales and et al. Unfolding the dimensionality structure of social networks in ideological embeddings. 2021.

[2] Yehuda Koren and et al. Matrix Factorization Techniques for Recommender Systems. 2009.

FUTURE RESEARCH

This work :

- Mainly **linear relations**
- General tendencies

Future works :

- Different relations (e.g.: random trees).
- **Measure the impact** of each *specific* attitude on the result of **each recommendation**.

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