Relations between political preferences of users and recommendation algorithms.

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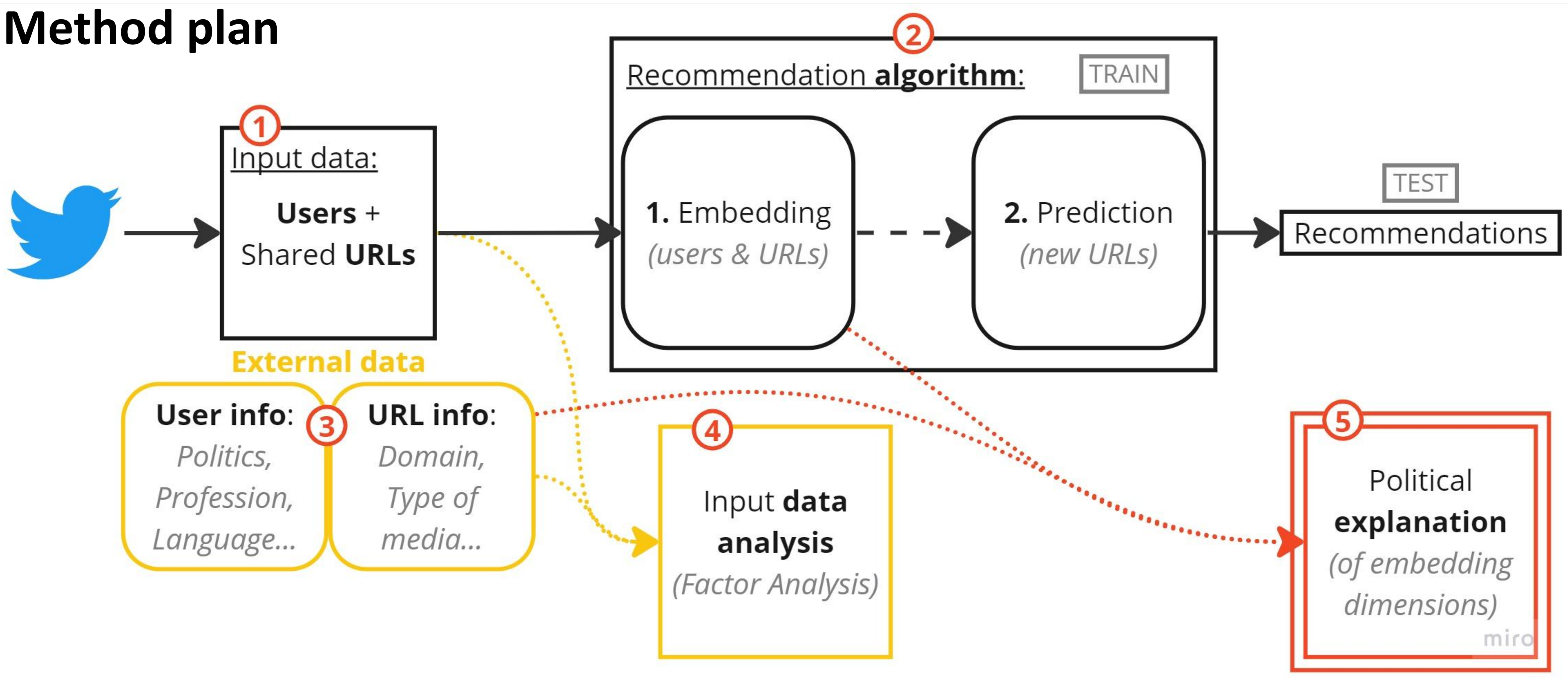
Abstract

- Recommender systems in social platforms attract attention in part because of their potential impact over political phenomena.
- We propose a method to explain recommendation with political variables.
- We train a collaborative filtering recommendation algorithm on real world twitter data.
- We leverage political opinion estimation to explain the embedding learned by the algorithm.

State of the art

	Target of explanation	Source of explanation
State of Art [1]	Result of recommender	Input features
Our method	Latent embedding of recommender	External political data

Method plan



Results

Analyzing the recommendation algorithm (1-2) we see that, while in the input data determinants are profession and language (3-4), in the algorithm embedding some dimensions are strongly related only with political attitudes (5).

Conclusion

In this work we introduced a new explanation method based on comparing the algorithm latent embedding with external data. Applying this method on an algorithm trained on twitter data, we show that it is possible for a standard recommendation algorithm to learn and leverage political attitudes of users.

Recommendation algorithms can **learn** and leverage **political opinions** of users on social medias.

Political explanation method for recommendations on twitter.

Website & Contact

1 Data collection

We collect data from Twitter.

- 29.373 Users
- 32.639 Items (URLs shared by users)
- 3.277.738 Posts (tweets)

Input data: Users-Items matrix with the number of times each user shared each URLs.

2 Recommendation algorithm

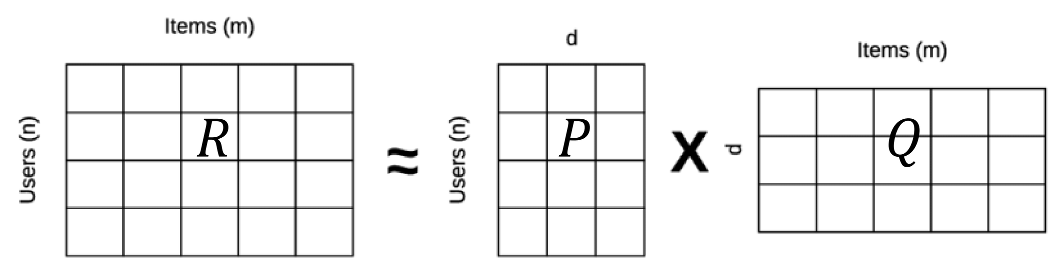
We train a recommendation algorithm on the input data.

	Step	Method
1	Create an *embedding space* with users and items	Non-negative Matrix Factorization
2	Predict new sharing	Scalar product
3	Accuracy test	Hits@10 (proportion of best items guessed)

Embedding:

Collaborative Filtering Hypothesis : similar users like similar content.

Non-negative Matrix Factorization method [2]:



$$\min_{P\in\mathbb{R}_+^{n\times d},\,Q\in\mathbb{R}_+^{m\times d}} \|R - PQ^T\|_2^2$$

With R users-items matrix, P user embedding, Q item embedding.

Performance: $Hits@10[\text{test–set}] = 0.35$.

Bibliography

[1]: Tintarev, N., & Masthoff, J. (2007). A survey of explanations in recommender systems.
[2]: Koren, Y., et al. (2009). Matrix factorization techniques for recommender systems.
[3]: Ramaciotti Morales, P., et al. (2022). Inferring attitudinal spaces in social networks.
[4]: Cointet, J. P., et al. (2021). Uncovering the structure of the French media ecosystem.

3 User & URL information

*We collect **external data** in order to explain the input data structure and the algorithm embedding.*

User data:

- **Political Attitudes:**
  - Left - Right &s Antielite-Salience (attitude toward elite institutions).
  - Estimated from the French Member of Parliament followed by each user. According to the existing methodology [3].
- **Professional class:**
  - Auto declarative profession on twitter user description.
  - Recognized with keywords + human supervision.
  - Classified according to the French official classification CSP2020.
- **Language:**
  - Main language of the twitter user description.
  - Recognize with NLP tools.

URL data:

- **Media category:**
  - Media category of the URL according to existing classification [4].

4 Input data analysis

We try to understand the sharing behaviors in the input data before training.

Method:

1. Correspondence Analysis of Users-Items matrix to reduce to 3 main dimensions
2. Factor Analysis of the main dimensions respect to the external data

Results:

Dimension	Main determinant
1	Business, IT and Administration Professionals
2	Elected officers and political representatives
3	Language (Spanish, Catalan)

5 Political explanation

We look at statistical relations between the learned embedding dimensions and the external variables.

Learned dimensions 3 and 4 present significative statistical correlation with political attitudes.

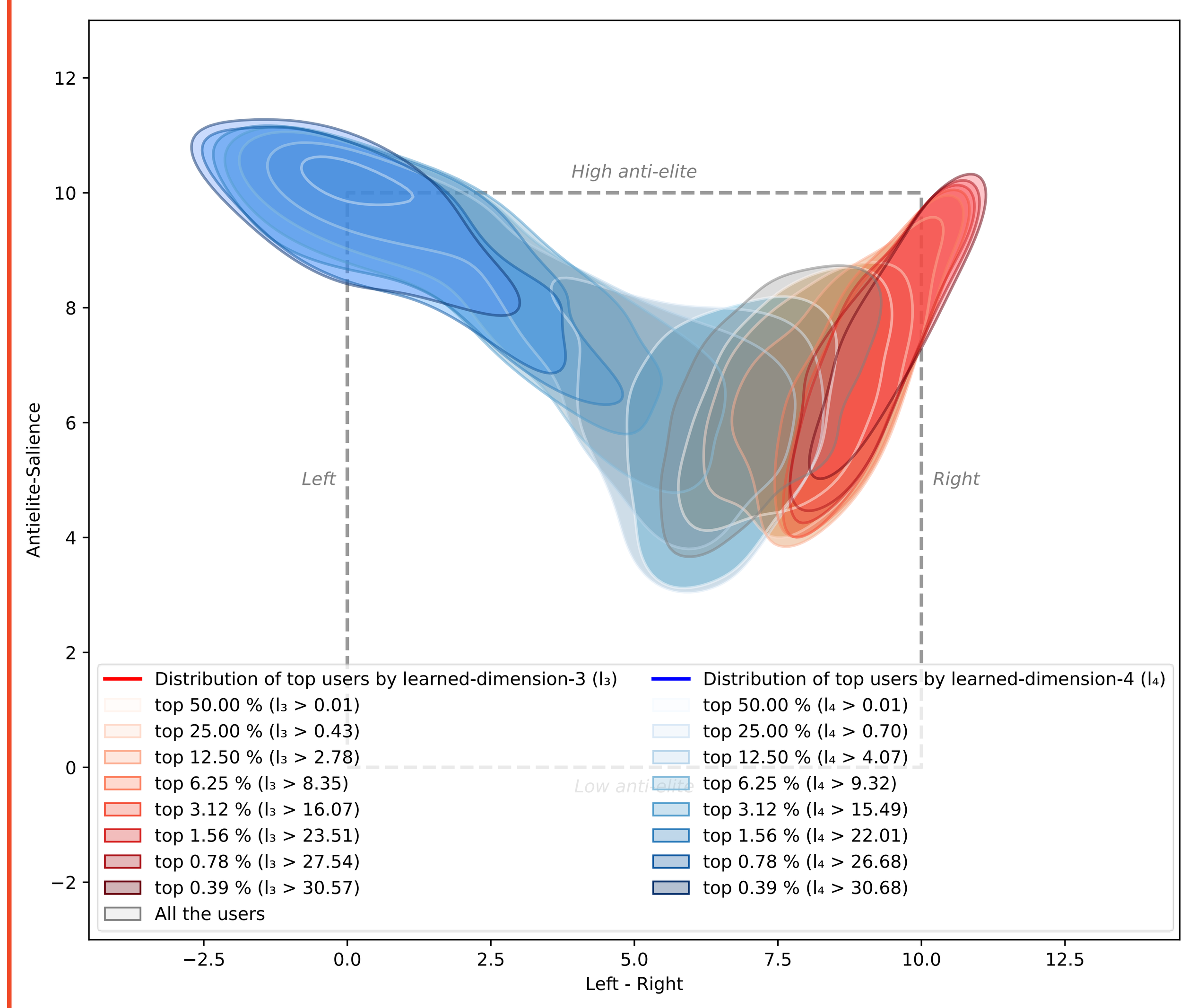


Fig 1. top users in learned-dimension-3 (right wing) and top users in learned-dimension-4 (left wing + antielite)

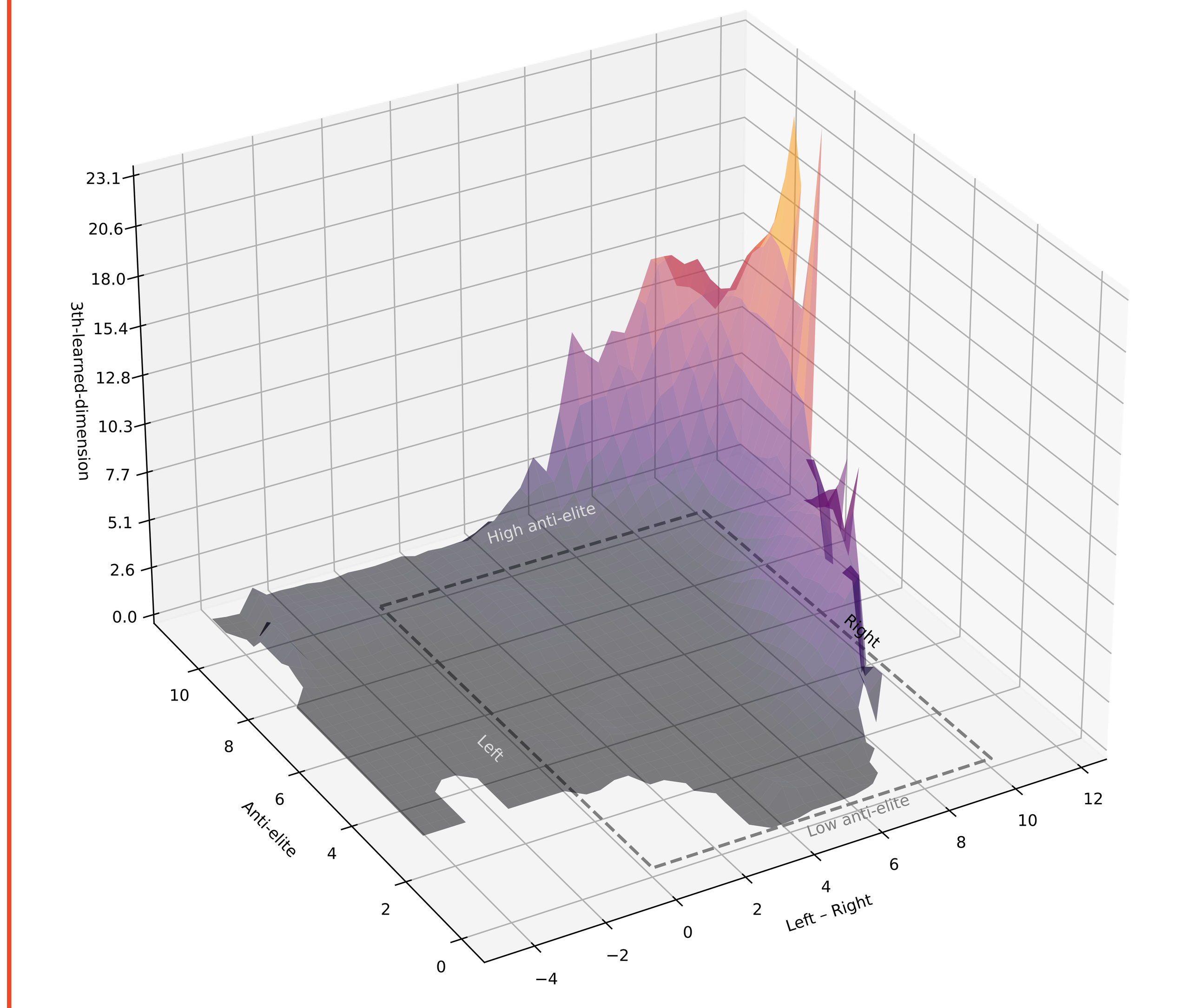


Fig 2. Expected value of learned-dimension-3 depending on political attitudes.