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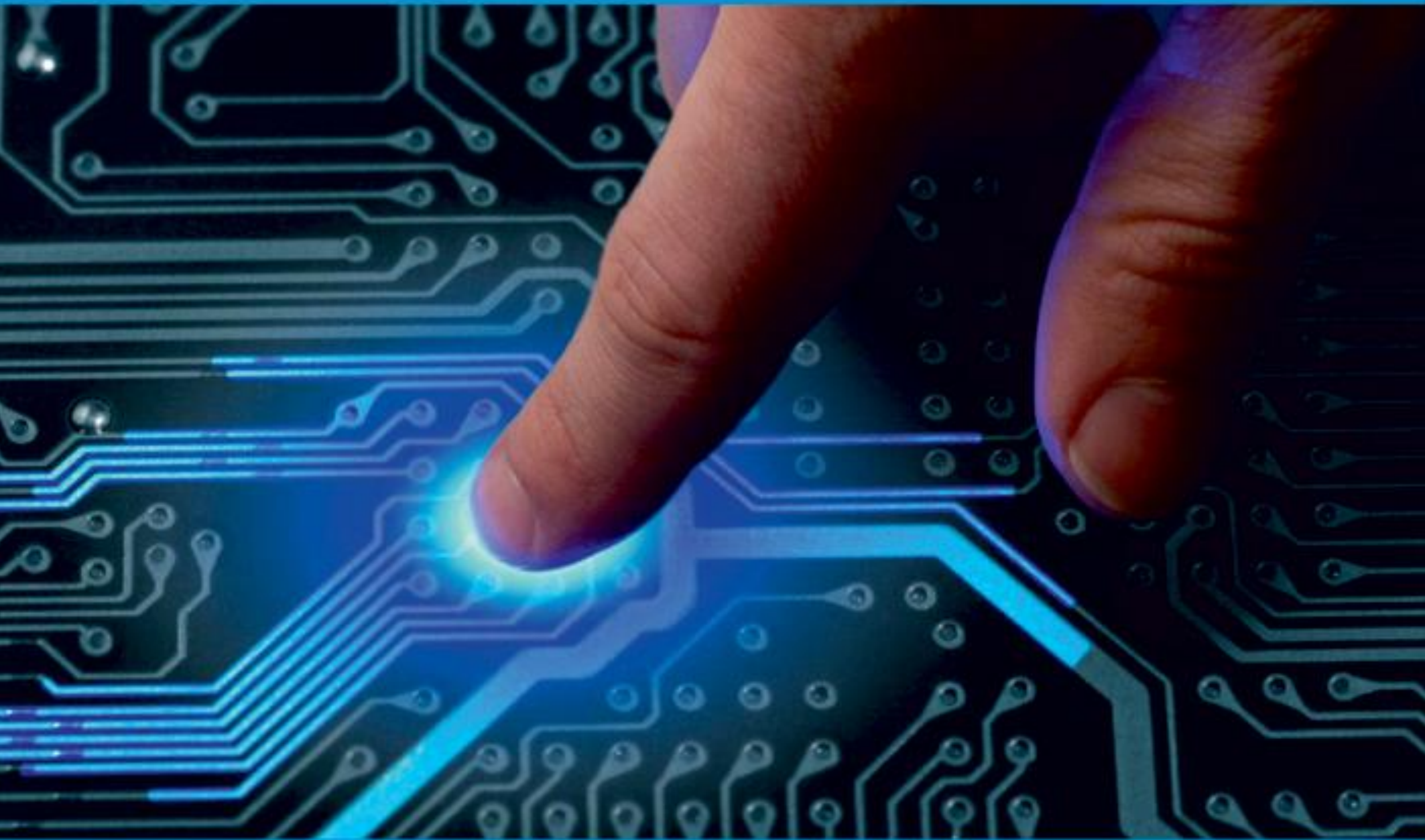

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Depolarized Recommendation System for Social Media

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ABSTRACT: Recommendation systems working today behind social media platforms aim at personalization of the user feed. The content recommended to users is tailored to their tastes and preferences. However, over-personalization of content can lead to the formation of echo chambers and thus polarization on social media. Polarization in politics on social media is especially harmful as it leads to a tremendous lack of understanding. People become more entrenched in their political opinions and less open to listening to opposing views. It discourages people from reaching a compromise and instead promotes an uncivil exchange of debates. Hence, it is imperative that social media platforms recommend balanced content i.e. personalized as well as neutral or opposing content, thus encouraging users to interact with diverse topics. This will ensure a positive discourse on social media, especially in the field of politics. Our project aims to develop a recommendation system for social media that will estimate users' political polarity and recommend content accordingly. We calculate user polarity by analyzing the political posts made by the user and using it as a parameter in the recommendation system.

KEYWORDS : Recommender System, Polarization Detection, Machine learning, Echo Chamber, Data Science.

I. INTRODUCTION

Polarization is the formation of tightly linked groups of people who share similar ideologies, interests, and behaviours. Polarizing topics such as politics give rise to such opposing groups on social media platforms, and as a result the dislike between people with opposing views grows each day. In online social networks, this characteristic tends to be stronger because users start to be selectively exposed to similar points of view through mechanisms whose goal is to optimize engagement. Our solution to this is to create a recommendation system that can detect polarization and recommend neutral / opposite content to the user if the user wants to see more variety in their content. Which will help in reducing the echo chamber effect and foster a healthy communicating network on social media.

Polarization within social networks plays a major role in politics. Users supporting a political party tend to interact with content that favours their party. This leads to formation of echo chambers which are tightly formed groups within the social network that are affiliated with only one political party. The network in this case becomes highly centralized. People in an echo chamber are recommended the same kind of biased content. Hence, even if they wish to explore more neutral or opposite content, doing so takes more time. The social impact of polarization is that people belonging to opposing groups never get a platform to positively exchange ideas and reach a compromise or a moderate opinion. Despite social media being a platform for communication, polarization has made exchange of ideas, especially political, a conundrum. A neutral user who shows even a little interest in any of the groups will immediately be pulled into the echo chamber and the content recommended to the user will be biased. This will influence the user's political mindset rapidly. Hence, a recommendation system that recognizes the polarity of the user and content, and makes the right decision on the type of content to recommend, is needed.

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II. RELATED WORK

Polarization is a part of our human nature. The paper [1] Proposed a centrality metric that enables the identification of highly central brokers (bubble reachers) that reach users with diverging political opinions. Another effort in this field is done by [3] A polarization-aware recommendation based on NMF that succeeds to cover items from the opposite view after a few iterations and can broaden the viewpoint spectrum even faster.The paper follows the methodology of collaborative filtering. Unlike traditional NMF recommender systems, the proposed system uses user-polarity score while recommending items to users. Going further in this view, in the paper [2] Proposed a model based on the user-tweet bipartite graph for user stance detection. Started with social media data regarding the 2020 US presidential elections. Then, annotate the tweets based on manually tagged hashtags and label the user's stance according to the label ratio. They Started with dataset and data labelling methods. Then proposed the construction of the user-tweet bipartite graph. Finally, presented how the model learns the representation of nodes by a homogeneous-heterogeneous joint information aggregation mechanism. Technology used :- Bipartite Graph Construction, DoubleH.

III. METHODOLOGIES USED

The various methodologies used in this project are:

A. *Collaborative Filtering:* Collaborative filtering is a methodology in recommendation systems that overcomes the limitations of content-based filtering. It leverages the similarity between users and items simultaneously to make recommendations. This approach analyzes user-item interactions, such as ratings and reviews provided by the users to identify similar users. Here, we use collaborative filtering to analyze hashtags used by users. It then recommends items based on the preferences of similar users or items.

B. *Non-Negative Matrix Factorization:* NMF decomposes the user-item matrix into two lower-rank non-negative matrices: a user-feature matrix and an item-feature matrix. NMF enforces non-negativity constraints on the factor matrices, which makes the decomposition suitable for representing non-negative data like preference scores. Here, we implement the recommendation system using NMF which is modified to incorporate user polarity score.

C. *Cosine similarity :* It is a similarity measure that quantifies the similarity between two vectors in a vector space. It calculates the cosine of the angle between two vectors, ranging from -1 to 1, where 1 indicates complete similarity, 0 indicates absolutely no similarity, and -1 indicates complete dissimilarity.

D. *K-Means clustering:* It is an unsupervised machine learning algorithm used to cluster data points into groups/clusters based on their similarity. The goal of K-Means clustering is to divide the data into K clusters, where K is a pre-defined number chosen by the user. In this case, clusters indicate the political labels of the hashtags.

E. *TF-IDF :* Term Frequency-Inverse Document Frequency (TF-IDF) is a widely used technique for feature extraction in text analysis. It represents text documents as numerical vectors, where each feature corresponds to a term in the document collection.

F. *PCA:* Principal Component Analysis (PCA) is a dimensionality reduction technique commonly used in machine learning and data analysis. It reduces a high-dimensional dataset into a lower-dimensional dataset while retaining as much information as possible. We use PCA for feature selection.

IV. PROJECT IMPLEMENTATION

A. DATA COLLECTION:

The data collected is scraped from Twitter, for our selected use-case, the data collected contains tweets by users pertaining to the US 2020 elections. Tweets were scrapped from September 2020 to June 2021 using top hashtags trending at the time such as #Trump2020, #VOTE, #Vote, #vote, #Election2020, #Biden, #Debate2020, #VoteBlueToSaveAmerica, #BidenHarris2020, #Trump. Each hashtag was used to scrape around 1,00,000 tweets which resulted in a total of 511082 tweets regarding the US 2020 presidential elections. Data was first formatted by converting columns to their respective data types, resetting index, and shuffling rows to uniformly spread data pertaining to each hashtag.

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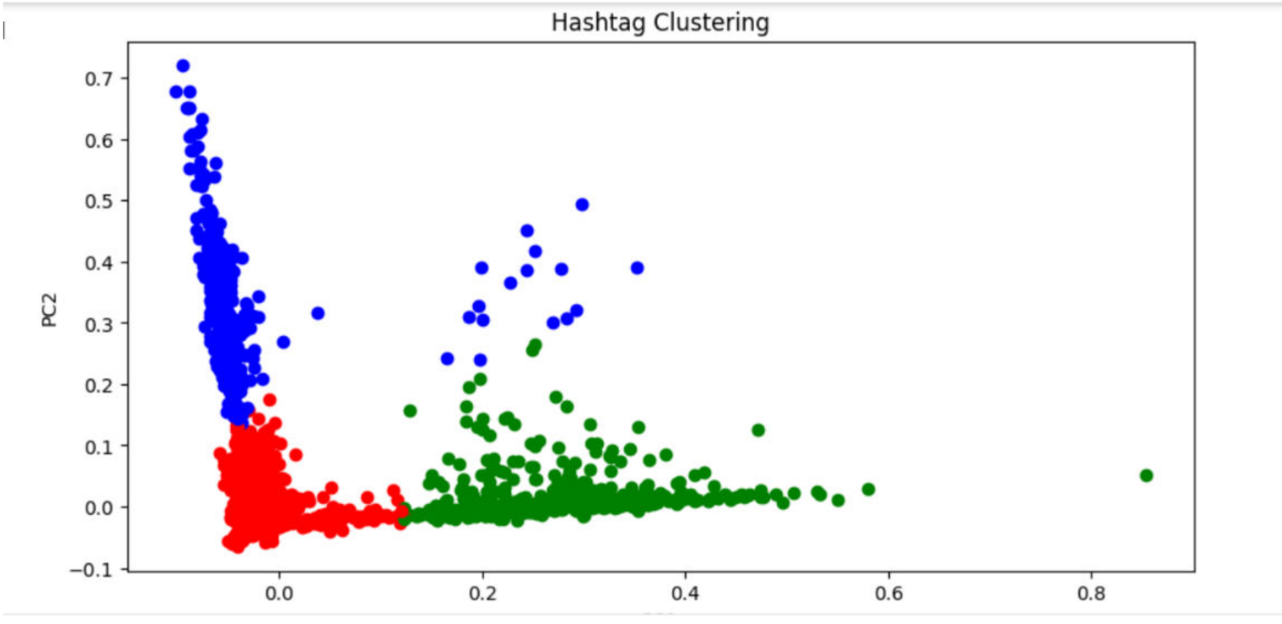
A sample of the data was taken for further processing by the method of random sampling. It was cleaned by removing null values, selecting only English tweets, removing emojis and emoticons, and extracting hashtags from each tweet. A separate column was made to store hashtags used in each tweet in the form of a list of hashtags. The total data finally included 12120 tweets.

B. Hashtag clustering:

Before calculating user polarity scores, we first clustered the hashtags according to their political leaning as "Right-wing", "Left-wing", and "Neutral", where:

- Right-wing ideology emphasizes notions such as authority, hierarchy, order, duty, tradition, reaction and nationalism.
- Left-wing ideology emphasizes ideas such as freedom, equality, fraternity, rights, progress, reform and internationalism.
- Neutral refers to a non-right wing and non-left wing leaning.

The purpose of hashtag clustering is to identify the type of hashtags used by each user. We extracted 8140 unique hashtags out of the total dataset. The hashtags are first vectorized using the Term Frequency - Inverse Document Frequency (TF-IDF) method and n-grams. The features extracted using the TF-IDF process represented unique tri-grams from all the hashtags. Here, each hashtag is divided into tri-grams to ensure efficient feature selection. Out of thousands of features generated, only 100 significant features were chosen using Principal Component Analysis (PCA). The resultant matrix contained 100 features as columns, unique hashtags as rows and their respective TF-IDF scores. This resultant matrix was used to cluster hashtags.



Hashtag Clustering [fig.1]

C. User polarity estimation:

The next step was to determine user polarity scores for each unique user based on the hashtags they used in their tweets. This was done on a weekly basis. The dataset has data from July 2020 to September 2021, however only a few weeks before and after the election showed major activity.

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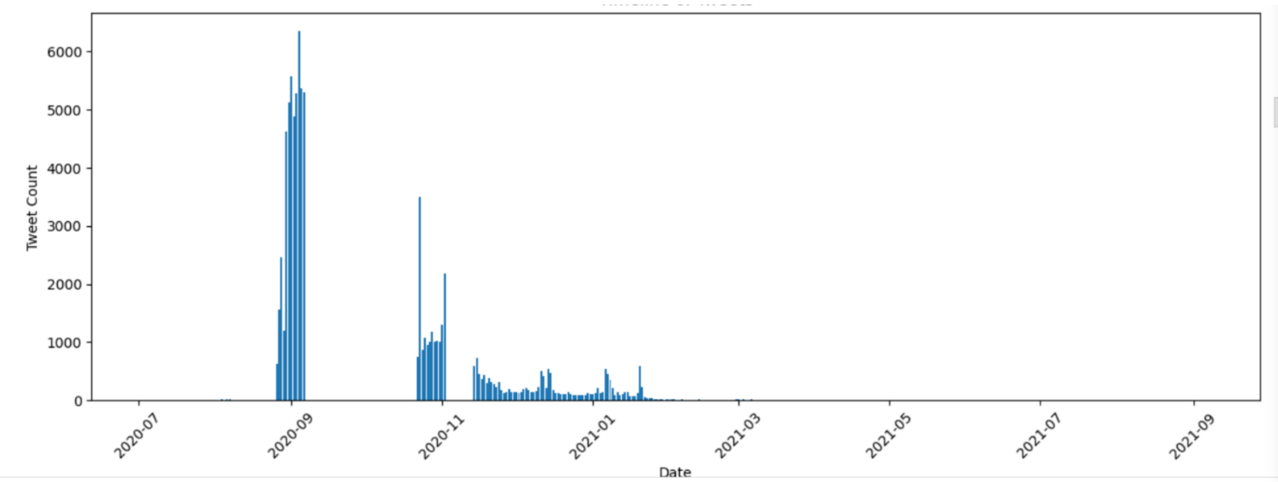

Timeline of users' tweets [fig.2]

As seen in the above figure, major activity can be seen from September 2020 to January 2021. Hence, we divided the above sub-set of data into ten weeks to find out the active users and calculate their user polarity. Active users here were users with more than five tweets per week. Others were removed from the dataset. By doing this, we obtained 1500 unique users.

For each of these users, a list of hashtags used in all of their tweets for the week was created, and their polarity (P(H)) was calculated using formula:

$$P(H) = \frac{|H_R| \times W_R - |H_L| \times W_L}{|H_L| \times W_L + |H_N| \times W_N + |H_R| \times W_R},$$

Polarity score [fig.3]

where HL, HN and HR are the hashtag multisets (a set that allows for multiple instances for each of its elements) for classes "L", "N" and "R", respectively. WL = avg(|HN |,|HR|)/|H|, WN = avg(|HR|,|HL|)/|H|, and WR = avg(|HL|,|HN |)/|H| are the weights for classes "L", "N" and "R", respectively.

D. Depolarized Recommendation System Using NMF

The basis of the system is Non-Negative Matrix Factorization (NMF). A classical NMF comes under Collaborative filtering. It divides the user-item matrix of size *m x n* into two matrices *W* and *H* each having dimensions *m x k* and *k x n* respectively. NMF aims to decompose the original matrix into two lower-rank matrices: a user-feature matrix and an item-feature matrix. The user-feature matrix represents how strongly each user is associated with each latent feature, while the item-feature matrix represents how strongly each item is associated with each latent feature. The key characteristic of NMF is that it enforces non-negativity in both the user-feature and item-feature matrices. This constraint ensures that the factorization remains interpretable, as negative factors are not allowed. By constraining the matrices to be non-negative, NMF can capture additive relationships between users, items, and latent features.

Once the matrix is factorized, the recommendation process involves finding the most suitable items for a given user. This is achieved by reconstructing the original matrix using the user-feature and item-feature matrices and then identifying the items with the highest predicted ratings for the user.

Our goal is to recommend opposing or neutral content. This is achieved by incorporating user polarity scores while recommending items.

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V. ALGORITHM DETAILS

Algorithm: Non-negative Matrix Factorization (NMF)

Input: -V: Matrix to be factorized- k: Number of latent features

Output: - W: User-feature matrix - H: Item-feature matrix

1. Initialize random non-negative matrices W and H with appropriate dimensions:

   1.1. W: Randomly initialize a matrix of size m x k, where m is the number of users.

   1.2. H: Randomly initialize a matrix of size k x n, where n is the number of items.

2. Repeat until convergence or maximum iterations reached:

   2.1. Update the user-feature matrix W:

   - Compute the numerator term: V * H.T
   - Compute the denominator term: W* H* H.T
   - Update each element of W: W_new = W * (numerator / denominator)

   2.2. Update the item-feature matrix H:

   - Compute the numerator term: W.T * V
   - Compute the denominator term: W.T * W * H
   - Update each element of H: H_new = H * (numerator / denominator)

   2.3. Calculate the reconstruction error:

   - Compute the Frobenius norm of V - W * H

   2.4. Check convergence criteria:

   - If the reconstruction error is below a predefined threshold or the maximum number of iterations is reached, exit the loop.

3. Return the user-feature matrix W and the item-feature matrix H.
4. Generate recommendations using polarity scores:

   4.1. Multiply the element-wise product of W and polarity_scores by H to obtain the recommendations matrix.

   4.2. The recommendations matrix represents the predicted ratings or scores for all users and items.

5. Select top 100 recommendations for each user:

   5.1. Sort each row of the recommendations matrix in descending order.

   5.2. Select the top 100 items with the highest scores for each user.

   5.3. Store these top 100 recommendations in the top_100_recommendations matrix.

1. Return the top_100_recommendations matrix.

VI. RESULT

We implemented the depolarized recommendation system on an environment of 1498 users and around 8000 unique hashtags. To compare the working of our proposed model, we implemented another recommendation system in the same environment. Both recommendation systems had the same parameters: number of components set to 10 and maximum iterations set to 500.

As shown in figure 4, both systems recommend items based on the given environment. However, our proposed system (red), recommends items that are opposed to the items recommended by the traditional recommendation system (green). There are also common items recommended by both the systems that indicate neutral content.

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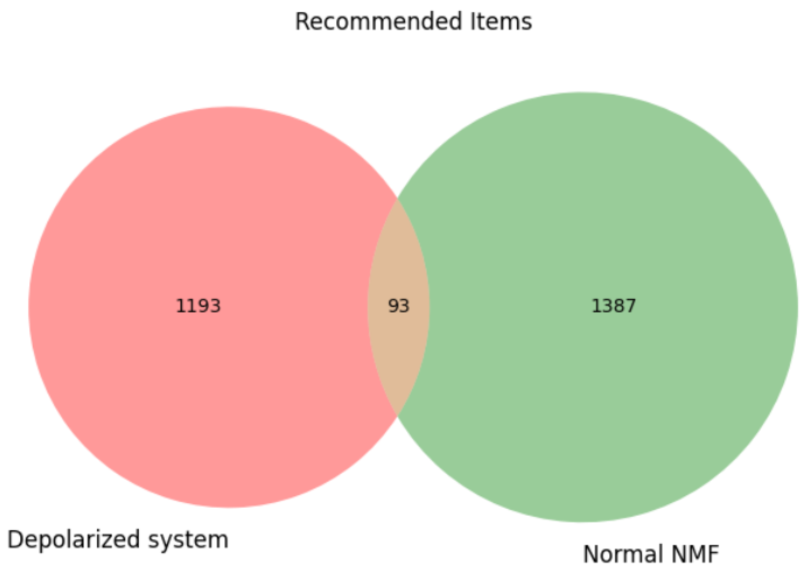

Polarized Vs. Depolarized Recommendation System [fig.4]

VII. CONCLUSION

In real-life, polarization is an important phenomenon, with serious consequences, particularly on social media. Thus it is important to understand how machine learning algorithms, especially recommender systems, behave in a polarized environment; and to this end it is important to quantify polarization in existing and new data sets. Our work is an essential step toward quantifying and detecting polarization in ongoing ratings and in benchmark data sets, and to this end, we used our developed polarization detection pipeline to compute the polarization prevalence of several benchmark data sets.We proposed a system that detects polarized groups, recommends neutral content & creates an egalitarian network of users. It is our hope that this work will contribute to supporting future research in the emerging topic of designing and studying the behaviour of recommender systems in polarized environments.

VIII. FUTURE WORK

The future scope of a depolarized system in the political domain addresses the challenges associated with political bias, echo chambers and fostering a more informed and balanced political discourse.

Following are some potential areas of development:

- *Cross-ideology recommendation and encouraging diverse political participation :* A depolarized recommendation system strives to recommend content from different political perspectives which allows an user to have a broader range of viewpoints and bring up a more balanced understanding of political affairs. Future systems can go beyond content recommendations and encourage users to engage in constructive political discussions and participate in platforms that promote diverse perspectives.
- *Fact-checking and misinformation detection:* Rumours and fake news are prevalent in the political domain; however, future systems can embed fact-checking mechanisms to verify the correctness of political content. By flagging misinformation and fostering reliable sources, depolarized systems can contribute to combating the spread of false information. Future scope of depolarized systems lies in promoting diverse perspectives, combating misinformation, providing transparency and fostering user engagement. By addressing these areas, we can aim to develop a recommendation system that contributes to a more informed and balanced political landscape.

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REFERENCES

1. Kobellarz, J.K., Broćić, M., Graeml, A.R. *et al.* Reaching the bubble may not be enough: news media role in online political polarization. *EPJ Data Sci.* 11, 47 (2022).
2. Chong Zhang and Zhenkun Zhou and Xingyu Peng and Ke Xu et al. DoubleH: Twitter User Stance Detection via Bipartite Graph Neural Networks. arXiv. cs.SI. (2023)
3. Badami, Mahsa, and Olfa Nasraoui. "PaRIS: polarization-aware recommender interactive system." In *Proceedings of the 2nd Workshop OHARS*. 2021.
4. Cohen, R., & Ruths, D. (2021). Classifying Political Orientation on Twitter: It's Not Easy!. *Proceedings of the International AAAI Conference on Web and Social Media*, *7*(1), 91-99.
5. Ko, Hyeyoung, et al. "A survey of recommendation systems: recommendation models, techniques, and application fields." *Electronics* 11.1 (2022): 141
6. Faroughi, Azadeh & Morichetta, Andrea & Vassio, Luca & Figueiredo, Flavio & Mellia, Marco & Javidan, Reza. (2021). Towards website domain name classification using graph based semi-supervised learning. Computer Networks. 188. 107865. 10.1016/j.comnet.2021.107865.
7. Xiaoyuan Su and Taghi M. Khoshgoftaar. 2009. A survey of collaborative filtering techniques. Adv. in Artif. Intell. 2009, Article 4 (January 2009).
8. M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

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