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The Study on Visualizing the Impact of Filter Bubbles on Social Media Networks*

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Abstract

In this study, we delve into the effects of personalization algorithms on the creation of "filter bubbles," which can isolate individuals intellectually by reinforcing their pre-existing biases, particularly through personalized Google searches. By setting up accounts with distinct ideological learnings—progressive and conservative—and employing deep neural networks to simulate user interactions, we quantitatively confirmed the existence of filter bubbles. Our investigation extends to the deployment of an LSTM model designed to assess political orientation in text, enabling us to bias accounts deliberately and monitor their increasing ideological inclinations. We observed politically biased search results appearing over time in searches through biased accounts. Additionally, the political bias of the accounts continued to increase. These results provide numerical evidence for the existence of filter bubbles and demonstrate that these bubbles exert a greater influence on search results over time. Moreover, we explored potential solutions to mitigate the influence of filter bubbles, proposing methods to promote a more diverse and inclusive information ecosystem. Our findings underscore the significance of filter bubbles in shaping users' access to information and highlight the urgency of addressing this issue to prevent further political polarization and media habit entrenchment. Through this research, we contribute to a broader understanding of the challenges posed by personalized digital environments and offer insights into strategies that can help alleviate the risks of intellectual isolation caused by filter bubbles.

Keywords : Information Society, Personalization Algorithms, Filter Bubble, Liberal and Conservative Bias

Major Classification Code : Artificial Intelligence, etc

1. Introduction

Algorithms of large online platforms such as Facebook are a factor that intensifies political polarization, and the algorithm's personalization function is evaluated as providing content selectively according to users' tastes and habits, narrowing the scope of thinking, and deepening the division of society. Regardless of what users perceive, users are surrounded by numerous personalization algorithms that are closely located in the real world and directly or indirectly affect users. Personalization algorithms also analyze users' past behavioral data and suggest activities or experiences that users can participate in, such as physical product or service recommendations, travel destination recommendations, restaurant reservations, and event participation. In addition, information or advice that directly

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affects users' daily lives, such as health, exercise, and financial management, is provided through personalization algorithms and influences users to make and act in the real world through information and recommendations received in the digital environment. Based on this, users can make promising decisions, save time and money, and have the advantage of living a little more prosperous and comfortable. However, users encounter only limited information on a limited topic selected by a machine called an algorithm, not a human, among a lot of information. Information on social issues that should be of interest is relatively pushed back from priorities, and the user's view becomes narrower. Ultimately, the user is trapped in a filter bubble in which the user's view becomes narrow due to the inability to access various opinions.

At a TED conference in 2011, political activist Eli Pariser preached the dangers of online filter bubbles. The filter bubble is a metaphor that refers to a phenomenon in which Internet users are caught in a narrow 'bubble' formed by algorithms of platforms such as Google. Around the same time, the echo chamber metaphor of legal scholar Cass Sunstein was also attracting attention. The echo chamber was a metaphor that compared homogeneous groups formed on the Internet to an anti-emotional. Just as a voice in an echo chamber sounds multiple times by reflecting it, it means that people with similar tendencies on the Internet gather to repeat and amplify only opinions that agree with each other (Sunstein, 2001). The two metaphors deepen political polarization. Political polarization is a phenomenon in which the proportion of the middle decreases while polarizing conservatives into more conservatives and progressives into more progressives, which is known to threaten democracy in that it hinders the diversity of perspectives and makes productive communication difficult (Chae, 2016). Due to the filter bubble, users have relatively fewer opportunities to encounter opinions from people who are contrary to them, and the more the user's political ideology is biased to one side. It is an obstacle to deepening political confrontation among members of society and reaching social consensus.

This paper is limited to the proof of filter bubbles in theory, such as traditional recommendation systems for filter bubbles, and will present previous studies that do not have experiments through personalized algorithms that are closely related to users such as Google personalized search algorithms and Facebook newsfeed, and will increase the persuasiveness of the results by experimenting with Google's personalized search, which has a great influence on people's political views. To show that the filter bubble becomes more severe as the person with biased views uses the personalization algorithm, deep learning model design, political-related words are used, and the behavior that people with political views can do is reproduced to identify the nature and number of links, quantifying them, and numerically analyzing whether personalization algorithms contribute to political polarization by actually creating filter bubble phenomena and exposing users to their preferences. In addition, we will reveal the problems caused by the filter bubble, explore solutions to them, and seek ways to allow users to access more diverse information (Jeon et al., 2018).

2. A Related Study

T. T. Nguyen et al. identified the factors that form the filter bubble. Filter bubbles mainly occur in personalization algorithms, especially recommendation systems based on collaborative filtering. Collaborative filtering is a method of analyzing users' past behavioral data and recommending items that the users may be interested in. This study emphasized the need to recognize the filter bubble problem in the design and operation of the recommendation system and improve it in the direction of promoting diversity and balance. The influence of the collaborative filtering-based recommendation system on users was shown (Nguyen et al., 2014).

E. Bozdag often overlooks the voices of groups whose existing systems are structurally marginalized, which affects media diversity and fairness, and analyzes how users receive and share information from sources of various political spectrums to promote information diversity on social media (Bozdag et al., 2014).

M. Haim conducted a study on whether personalization algorithms form filter bubbles as Google News is used, and whether the news provided is directly affected by this. The effect of personalization through explicit factors, which are preferences set by users themselves in Google News, and implicit factors based on users' previous behaviors, on the diversity of news content and sources was analyzed. The study used input and output analysis methods to analyze the effects of personalization by changing users' surfing behavior or preferences and comparing the results of news provision accordingly (Haim et al., 2018).

3. An Experimental Method

The purpose of the experiment is to intentionally trap accounts in a filter bubble by making them have a progressive and conservative character through politically biased behavior and to prove the phenomenon that the filter bubble intensifies. To form a filter bubble, Google's personalization search, one of the personalization algorithms, is used. The progress of the experiment is to run one search for political bias to make the account politically biased, a search for bias, and a search for bias, and then to compare the degree to which the account fell into the filter bubble, the search for scoring is performed.

IBC (ideological book crop), a collection or database of books with specific ideological perspectives created to analyze the ideological trends of search results, and long-term memory (LSTM) classify and analyzes headlines that indicate political conservative, progressive, or other ideological trends, including news headlines and headlines extracted from article titles to analyze language usage and framing of headlines to identify specific ideological biases. If there is a link classified as progressive, it is called a politically biased search word. If there is a link classified as progressive because of the long short-term memory (LSTM) classifier that classifies and analyzes headlines that are entered, such as search words, web links, and article titles, into political categories such as progressive or conservative, accesses, and exits. If this process is repeated for 200 words, it is said that the search for bias was executed once.

After executing one search for bias, a method called "search for scoring" is executed to show that the account is more biased than before and to compare the degree of falling into the filter bubble. Each time a search for scoring is executed, 20 critical search words of the same word are searched, links of each search result are classified into an LSTM classifier, and the proportion of the progressive, neutral, and conservative links among all links are identified. It is said that the higher the proportion of progressive links in the progressive account than the proportion of progressive links in the conservative account, the greater the impact of the filter bubble on the search results.

3.1. Experimental Data

3.1.1. Politically Biased Search Words

Politically biased search terms are search terms used to make an account in a purely politically biased state. A total of 4 texts were generated by extracting data with 'progressive' and 'conservative' tendencies in the IBC and IHC. The selected search terms from a total of 4 texts were combined into 2 data sets according to political orientation, and overlapping search terms were removed in this process. However, if there were overlapping search terms in the list of 'progressive' and 'conservative', it was not removed. It was considered that there were search terms with both progressive and conservative characteristics, and that progressives also searched for conservative search terms, and the opposite occurred. Politically biased search terms are divided into liberal and conservative search words, and examples are shown in Table 1(Jeon et al., 2018).

Table 1: Examples of search words

	Liberal search words	Conservative search words
Politically biased search words	wage, health care, labor, social security, rape or incest, unemployment , insurance, young women workers, for the rich, wealthiest, labor, rich and poor	death tax, republican, free medical care, big government, heritage foundation, good and evil, tea party, redistribution, radical Islamism
Criteria search words	liberal, wage, tax cut, great depression, economic system, unemployment, federal government, energy source, climate change, gun control, crime, national security, conservative, free market, health care, free trade, housing problems, oil prices, administration, income tax, death tax, republican, free medical care, big government, heritage foundation, good and evil, tea party, redistribution, radical Islamism	

3.1.2. Criterial Search Words

Criteria search terms are search terms used to prove the process of turning an account in its pure state into a politically biased state. However, in the process of searching, the following conditions were considered and selected to prevent situations that are biased against one political orientation as much as possible. Medium-sized data within the IBC were extracted. Bias is prevented from being biased toward a specific orientation by selecting only search terms that exist in common in progressive and conservative search terms within politically biased search terms. After that, to effectively reflect the biased situation in the experimental results, 20 are selected from among them, excluding the cases included in the neutral search terms derived above. The final selected criteria search terms can be found in Table 1.

3.2. Political Ideology Analyzer

The political ideology analyzer is a text classifier that classifies the characteristics of text into 'conservative', 'neutral', and 'progress' in sentence units using the aforementioned LSTM model. To design this, various tools were used in the Python 3.5.3 environment. Scikit learning was used to utilize traditional machine learning techniques such as cross-validation, and NLTK (natural language tool kit), and space was used for text preprocessing and natural language processing. In addition, the LSTM, which is mainly used in this paper, was experimented with keras. The structure of the final model is shown in Figure 1. Starting with the input layer, it leads to a word embedding layer, an LSTM layer, and a fully connected layer, which is an output layer. It was learned as 7,396 progressive sentences and 8,275 conservative sentences in the IBC and IHC, a total of 15,671 sentences. Here, conservative sentences were labeled as 1 (positive), and progressive sentences as 0 (negative). The political orientation of the sentence was tried to be classified into three categories of 'progress', 'neutral', and 'conservative', but insufficient 'neutral' data resulted in a decrease in accuracy. As an alternative to this, sigmoid was used as an activation function of the dense layer, which is the final output layer, and values of 0.66 or more among the real numbers between 0 and 1 output as a result were classified as 'extremely conservative', and values of 0.33 or less were classified as 'progress', respectively, and values between 0.33 and 0.66 were classified as 'neutral'. The sentence used for learning the model consists of a total of 20,340 words. Word embedding was used for each word to reflect the relationship between other words. To apply this, a word embedding layer was separately placed to represent sentences using the GloVe vector (Pennington et al., 2014).

3.3. Search for Biasing

There are a few factors that influence Google's search, such as location, device type, past search history, cookie data, link type to be accessed, and the time it stays in that link. As above, search for bias is a method of politically biased behavior to make an account in its pure state politically biased state and proceeds as follows. 200 search terms in the same politically biased search term as the political tendency for each account to be biased are searched through that account. The selection of 200 search terms is made as follows. Politically biased search terms are assigned a number from 0 for each word by progressive and conservative. Each execution has 100 search terms searching for the same search term as the previous search term, and 100 search terms searching for a new search term. 200 words are selected in the same order as conservative and progressive 0 to 200, 100 to 300, 200 to 400 ... N-200 to N, N-100 to 200, 0 to 200. There are 607 progressive words and 693 conservative words, so the progressive account searches for the same search word every 6 repetitions of the bias search method, and the conservative account searches for the same search word every 7 repetitions. This action will continue to accumulate politically biased search word records in pure search logs, and Google algorithms will gradually provide more and more biased search results based on them.

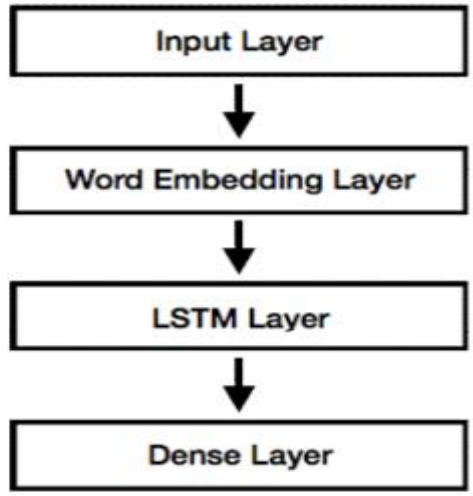

Figure 1: Structure of LSTM Text Classifier

At the same time, the LSTM model checks the political orientation of each link based on the title and summary of about 20 links within pages 1 or 2 for each search term. In the process, if the account is biased and the link's political orientation is the same, visit the link and give feedback to the Google Personalization Search Algorithm as if the political orientation is necessary. It is said that if the series of processes mentioned above was performed once for 200 search terms, it performed a search for bias once.

3.4. Searching for Scoring

Search for scoring is used to show that the account is more politically biased than before after executing a search for bias and is a method of identifying the number of links in the search result. To this end, the search for scoring searches for the same reference search terms in the progressive and conservative accounts obtained because of the search for bias, and each time a word is searched, the political bias of about 100 links on pages 1-5 is identified using the LSTM classifier. Among them, the number of links with progressive and conservative characteristics is identified.

4. The Results of The Experiment

4.1. Experimental Environment

The experimental environment was divided according to the political orientation aimed at each account. First, two new Google accounts with no information piled up were created.

When signing up for membership, both birthdays and residences were set the same as on January 1, 1991, and the United States, respectively, so the conditions excluding search terms were adjusted as much as possible.

The system environment is as follows. It was conducted on a Chrome web browser on the Mac OS 10.12 operating system. In addition, selenium, a web driver, was used to run a Chrome browser in a Python 3.5.3 environment, and when web scraping was required, the beautiful soup was mixed and used. The experiment is conducted in a way that continuously executes a search for bias, which is an act of trying to politically bias an account, and a search for scoring, which is an act of proving bias. Here, whenever the search for bias is completed, the search for scoring is executed immediately, and the 'bias' is measured through this. Here, it is said that as the 'bias' increases, the account is trapped in a filter bubble (Jeon et al., 2018).

4.2. Scoring System

The ratio of progressive links to conservative links in the search results for one reference search word is defined as the Score for one reference search word. It represents the proportion of progressive links among the sum of the number of progressive links and conservative links in one account. The score obtained from the progressive account is called score-lib, and the score obtained from the conservative account is called scorecon. Here, the reason it is irrelevant even if the standard is determined based on the progressive link is that the sum of the scores calculated based on the conservative link is always the same as 1. In this principle, when scorelib is higher than the scorecon in the progressive account, the proportion of progressive links is higher than that of the progressive account, whereas, in the conservative account, the proportion of conservative links is higher than that of the progressive account. Based on the Score according to each reference search word, the political state is determined through a series of processes as shown in Figure 2. Since there are a total of 20 scores of reference search words, 20 states are derived. If the values of scorelib and scorecon are the same, the superiority of the bias cannot be determined, so only if it is not, it is determined as a valid state. If the scorelib has a value greater than the scorecon among the valid states, it is determined as a politically biased state.

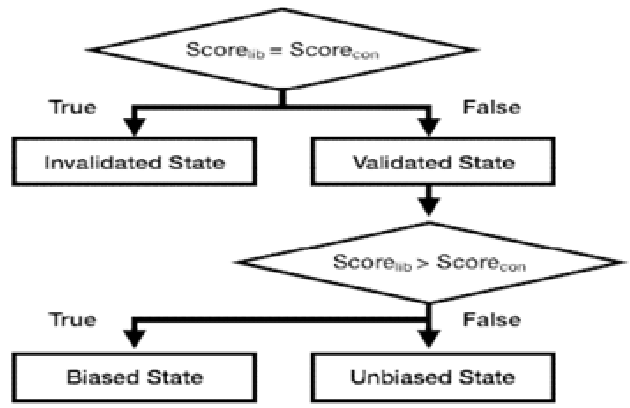

Figure 2: Block diagram in a possible state

The experiment is conducted by repeatedly performing a search for bias, a method of making an account politically biased. Based on the search results obtained above, the bias degree, which numerically represents the bias of the search results, shows a change in search results every certain period. However, when the values of scorelib and scorecon are the same, it is not suitable to indicate the change in political orientation, so when calculating the bias, only the states that did not take this into account were dealt with. The method of obtaining the bias is BiasDegree = Biased State / Validated State. The initial state of the account is measured and saved by executing a search for scoring before executing the search for bias for the first time. The point currently is called T0. After that, when the search for bias is executed and the search for scoring is measured again, it is named and saved as T1. Since the experiment is conducted as above and the time required to run the method is different for each account, the progressive account was conducted up to T25, and the conservative account was conducted up to T33, respectively. Each account executes a search for scoring up to T25 and T33 and accumulates information on all links in the search results obtained. Here, search results are not only affected by the time of the search, but also the bias measured based on the maximum amount of data is more reliable, so all results are considered. The accumulated results are classified according to the standard search term, political orientation, account type, and political bias of the link, and the proportion of links with progressive character is determined based on each number. After that, from T5 to T25 for progressive accounts and T33 for conservative accounts, all links are searched for scoring in the same way as above, the ratio of progressive links is determined, and bias is measured based on the number of search results obtained. The number of T10, T15, and T20 is also identified in the same way as above, and the bias is measured based on this. The first accumulated time point is constantly increasing by 5 as T0, T5, T10, ... T20.

Table 2: Political Ideology Analyzer Performance

	Accuracy	Precision	Recall	F1-Score
Bidirectional LSTM	0.733	0.744	0.721	0.732

This cycle is expressed as an observation cycle, and the observation cycle in this paper is 5. At the same time, in order not to be affected by the change in the total number of links considered, the percentage of progress in the search results was calculated based on the number, and the bias was calculated based on this.

Table 3: Total number of cumulative links from T0 to end, each score and status table

	liberal account			conservative account			state
criteria search words	lib links	con link	$Score_{lib}$	lib links	con links	$Score_{con}$	
administration	26	53	0.3	23	64	0.3	BS
climate change	213	0	1	287	0	1	IVS
conservative	26	24	0.5	30	33	0.5	BS
crime	74	150	0.3	90	201	0.3	BS
economic system	39	0	1	48	1	1	BS
energy source	136	22	1	184	2	1	UBS
federal government	9	10	0.5	13	14	0.5	UBS
free market	10	19	0.3	12	23	0.3	BS
free trade	21	12	0.6	28	13	0.7	UBS
great depression	11	57	0.2	14	76	0.2	BS
gun control	12	35	0.3	13	48	0.2	BS
health care	127	27	0.8	193	32	0.9	UBS
housing problems	0	39	0	0	47	0	IVS
income tax	55	28	07	74	33	0.7	UBS
liberal	32	176	0.2	34	234	0.1	BS
national security	21	0	1	30	0	1	IVS
oil prices	105	25	0.8	134	28	0.8	UBS
tax cut	209	5	1	274	4	1	UBS
unemployment	40	0	1	47	0	1	IVS
wage	16	79	0.2	29	96	0.2	UBS

4.3. Experimental Results

In this study, the political orientation of online links was classified using an LSTM-based text classifier, that is, a political ideology analyzer. The performance of the classifier was evaluated as accuracy, precision, recall, and F1-Score. In the research process, the initial state of the account was measured, and the search for bias was repeated to observe how the account bias changed over time. The ratio of liberal and conservative links obtained from the search results is shown as a score. Based on the score, the status of the account for the search term was classified. The change in bias was measured according to the observation period, and the results when the observation period was 10 and 5 were compared to confirm that the bias of the account gradually increased over time. Table 2 shows the performance of the political ideology analyzer using the LSTM model. According to Table 2, the accuracy of the analyzer is about 73.3%. Table 3 shows the accumulated number of links for each reference search word from T0 to the end of the experiment. Scoreib and Scorecon were calculated based on the number of links obtained from the progressive and conservative accounts, and based on this, the state of the search word was divided into biased state (BS), unbiased state (UBS), and invalid state (IVS).

Table 4 shows changes in the account state and scores (Scoreib, Scorecon) and bias degree for each search word at specific time zones T0, T10, and T20. The table shows that the bias degree increases over time.

Table 5 shows the change in the degree of bias for each observation period. It shows that the number of invalid states (IVS) remains constant, and the number of unbiased states (USB) decreases as the experiment proceeds, while the number of biased states (BS) increases. This means that the bias of the account increases over time.

These results numerically show that filter bubbles exist and that these bubbles are having a greater impact on search results over time.

Table 4: Scores and Status in T0, T10, T20

	T_0 to end			T_{10} the end			T_{20} to end		
criteria search word	$Score_{lib}$	$Score_{con}$	state	$Score_{lib}$	$Score_{con}$	state	$Score_{lib}$	$Score_{con}$	state
administration	0.329	0.264	BS	0.377	0.329	BS	0.333	0.325	BS
climate change	1	1	IVS	1	1	IVS	1	1	IVS
conservative	0.52	0.476	BS	0.344	0.333	BS	0.313	0.286	BS
crime	0.33	0.309	BS	0.336	0.306	BS	0.308	0.299	BS
economic system	1	0.98	BS	1	1	IVS	1	1	IVS
energy source	0.986	0.989	UBS	0.905	0.943	UBS	0.947	0.989	UBS
federal government	0.474	0.481	UBS	0.571	0.579	UBS	0	0.429	UBS
free market	0.345	0.343	BS	0.36	0.182	BS	0.4	0.231	BS
free trade	0.636	0.683	UBS	0.478	0.629	UBS	0.455	0.5	UBS
great depression	0.162	0.156	BS	0.18	0.149	BS	0.227	0.208	BS

gun control	0.255	0.213	BS	0.316	0.255	BS	0.375	0.265	BS
health care	0.825	0.858	UBS	0.819	0.84	UBS	0.892	0.874	BS
housing problems	0	0	IVS	0	0	IVS	0	0	IVS
income tax	0.663	0.692	UBS	0.635	0.667	UBS	0.65	0.628	BS
liberal	0.154	0.127	BS	0.156	0.146	BS	0.176	0.139	BS
national security	1	1	IVS	1	1	IVS	1	1	IVS
oil prices	0.808	0.827	UBS	0.833	0.828	BS	0.758	0.853	UBS
tax cut	0.977	0.986	UBS	0.953	0.978	UBS	1	0.947	BS
unemployment	1	1	IVS	1	1	IVS	1	1	IVS
wage	0.168	0.232	UBS	0.073	0.231	UBS	0.05	0.231	UBS
bias degree	0.5			0.5333			0.6667		

Table 5: Change in the degree of bias

T	T_0 to end	T_5 to end	T_{10} to end	T_{15} to end	T_{20} to end
IVS	4	4	5	5	5
UBS	8	8	7	6	5
BS	8	8	8	9	10
bias degree	0.5	0.5	0.5333	0.6	0.6667

5. Solution Plan

The solution to the account's filter bubble is as follows. When creating another virtual account separately from the user's account and searching for a word in the user's account, the virtual account converts each word into a list of numbers so that the computer can understand the meaning of the word, indicating the relationship between the words, and searching for words with a meaning that is related to the words searched in the real account through word embedding that shows the relationship between the words with similar meanings. This creates a virtual account with a personality that is opposite to the real account. If you are curious about the perspective of a person who is opposite to you on an issue, you can expect to have the advantage of a personalization algorithm and the advantage of easing the limitations of the filter bubble by showing it.

6. Research Presentation

The solution to the account's filter bubble is as follows. When creating another virtual account separately from the user's account and searching for a word in the user's account, the virtual account converts each word into a list of numbers so that the computer can understand the meaning of the word, indicating the relationship between the words, and searching for words with a meaning that is related to the words searched in the real account through word embedding that shows the relationship between the words with similar meanings. This creates a virtual account with a personality that is opposite to the real account. If you are curious about the perspective of a person who is opposite to you on an issue, you can expect to have the advantage of a personalization algorithm and the advantage of easing the limitations of the filter bubble by showing it.

6.1. Opposite Account

If current users search for political words through Google search, they can determine the political bias of the account, whether it is a progressive account or a conservative account. You can also determine how progressive an account is if it is a progressive account, and how conservative an account is if it is a conservative one. Then, we can create exactly the opposite account through this. You will be able to arbitrarily create an opposite account with a user account's bias and similar value to the Score but with the opposite orientation. If a user performs a search in this way, he or she will be able to enter the same word through the opposite account to obtain news or opinions from the opposite perspective of the user.

6.2. Account Diversity

In this study, the method used to measure the bias of account, and conservative accounts, but it is necessary to be conducted, but also conducted more methods such as progress and conservative accounting and conservative accounts. In this study, it can determine whether the account used in this study is used in this study.

In addition, the user's account and search results will be able to determine whether the user account and search results can be trapped in the user's account and search results. Diversity of links when the search, is also important, but diversity of the content of the content of the link is also important. It is the future research target to suggest that the content is biased and presented through research methods of determining whether the contents of the contents of each other.

The current state of these accounts for this accounting that the current state of the filter bubble is not recognized in the filter bubble, and the current status of personal algorithms and personal algorithms.

7. Conclusion

In this paper, we biased different accounts in their directions, checked them, and proved that filter bubbles can occur to users to numerically show the growing impact of filter bubbles on users. Furthermore, by presenting several studies to solve filter bubbles in the future, we proposed a way to solve the current big problem of bias and filter bubbles on the Internet. Through IBC and Political Polarization & Media Habits, IHC (Ideological Headlines Corp.) was created, and an LSTM model was designed to determine the political orientation of the text using IBC and IHC. To bias the account, a search for bias was deliberately performed. To prove that the account was biased as soon as the search for bias was conducted, the political bias of the links in the search results of the reference search term was investigated, and based on this, the bias was calculated, showing the increasingly biased process of the account. Through the process above, it was possible to prove that the filter bubble, which is a side effect of the personalization algorithm, exists through digital methods, and the seriousness was seen through the continuous increase in bias. The filter bubble phenomenon has a significant impact on access to information, and various approaches have been proposed to mitigate this phenomenon.

It is expected to lead to positive changes in the user's information search process and information ecosystem through actions that provide users with opposite opinions to users by creating virtual accounts of biased accounts or quantitatively measuring the bias of accounts and the diversity of search results.

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