Wikipedia’s Network Bias on Controversial Topics

Cristina Menghini, 1 Aris Anagnostopoulos, 1, Eli Upfal 2
1 Sapienza University of Rome, Italy
2 Brown University, USA
{menghini, aris}@diag.uniroma1.it, eli_upfal@brown.edu

Abstract

The most important feature of Wikipedia is the presence of hyperlinks in pages. Link placement is the product of people’s collaboration, consequently Wikipedia naturally inherits human bias. Due to the high influence that links’ disposition has on users’ navigation sessions, one needs to verify that, given a controversial topic, the hyperlinks’ network does not expose users to only one side of the subject. A Wikipedia’s topic-induced network that prevents users the discovery of different facets of an issue, suffers from structural bias. In this work, we define the static structural bias, which indicates if the strength of connections between pages of contrasting inclinations is the same, and the dynamic structural bias, which quantifies the network’s level bias that users face over the course of their navigation sessions. Our measurements of structural bias on several controversial topics demonstrate its existence, revealing that users have low likelihood of reaching pages of opposing inclination from where they start, and that they navigate Wikipedia showing a behaviour much more biased than the expected from the baselines. Our findings advance the relevance of the problem and pave the way for developing systems that automatically measure and propose hyperlink locations that minimize the presence and effects of structural bias.

1 Introduction

On Wikipedia, readers broaden their knowledge moving from page to page following hyperlinks (West, Paranjape, and Leskovec 2015; Lamprecht et al. 2016). Links placement on pages is the product of editors’ effort and determines what knowledge users are exposed to. Therefore, editors play the role of recommender systems and potentially embed their viewpoint, both in articles’ content and in hyperlinks. For this reason, Wikipedia is naturally subject to bias that we categorize into two kinds. On one hand, we have the content bias that is the bias in articles’ body and it is generally easy to detect and fix by editors ans bots. On the other hand, we have a more subtle form of bias, the structural bias, which is a form of bias ingrained in Wikipedia’s hyperlinks network and may impede users from exploring different opinions regarding a topic of interest.

The core objective of our work is to quantify structural bias. Despite Wikipedia’s community invested efforts to remove bias in pages’ content by employing a peer-review process (Wikipedia) and data-driven models (Kumar, West, and Leskovec 2016), the detection of structural bias has received no attention till now. We investigate its existence on a set of Wikipedia’s subgraphs induced by articles related to controversial topics and we assess its presence when the flows between pages expressing contrasting viewpoints are unbalanced, we define flows in Section 3.1. Figure 1 presents a sketch about a topic-induced network and the flows among its partitions. The one side arrow on the right of the figure represents the anti-reciprocated component, that represents the structural bias.

Other than investigating the existence of bias on articles’ network, we want to understand how and if Wikipedia’s users exposure to structural bias changes over the course of their navigation sessions. For this purpose, we distinguish between two types of bias.

Static structural bias reveals the reciprocity of connections among articles of different inclination and it is computed with an ad hoc version of the anti-reciprocity introduced by Squartini et al. 2013 (Section 3.1).

Dynamic structural bias describes the level of bias users are exposed to during their network explorations. It integrates the ad hoc anti-reciprocity with Markovian mod-
The analysis of the dynamic structural bias which proves

The introduction of structural bias issue on Wikipedia’s

instead of their separation.

strong and separated communities, to have meaningful and

users toward. And third, because of the intrinsic hierarchi-

aim to understand to which opinion the network channels

different from Wikipedia (i.e., Twitter). Second, they do not

approaches are limited in their applicability to Wikipedia for

Glance 2005; Garimella et al. 2018). However, these ap-

of different propensity (Conover et al. 2011; Adamic and

ability to reading only one opinion. For instance, users

are curious about United States politics, a topic that polar-

izes into Democratic and Republican. It is in Wikipedia’s

interest to ensure that the positions of links on pages facil-

itates reciprocal movement among articles of divergent lean-

(i.e., democratic or republican viewpoints) and not only

toward one of the options.

Because having a comprehensive view of the connections

among Wikipedia’s pages and detecting the network’s skew-

ness toward a viewpoint is a hard task for humans, the in-

roduction of advanced methods to quantify the structural

bias on Wikipedia is fundamental to preserve its reliability.

In previous work, researchers computed network bias

using metrics that evaluate the separation between nodes

of different propensity (Conover et al. 2011) [Adamic and

Glance 2005; Garimella et al. 2018]. However, these ap-

proaches are limited in their applicability to Wikipedia for

several reasons. First, they deal with network semantically
different from Wikipedia (i.e., Twitter). Second, they do not

aim to understand to which opinion the network channels

users toward. And third, because of the intrinsic hierarchi-
cal modular structure of Wikipedia [Brandes et al. 2009]

Lizorkin, Medelyan, and Grineva 2009], which implies

strong and separated communities, to have meaningful and

befitting metrics we have to flip the question, looking at the

strength of connections among divergent propensity pages

instead of their separation.

Contributions. Our main contributions are the following.

- The introduction of structural bias issue on Wikipedia’s

network.
- The definition of methods that measure structural bias on

general networks (Section 3).
- The collection of topic-induced networks for several con-

troversial topics (Section 4).
- The demonstration of the existence of static structural bias

on a collection of networks related to controversial topics

(Section 5.1).
- The analysis of the dynamic structural bias which proves

that users are strongly biased toward one side of the topics

(Section 5.2).

Project repository. We will make code, data, and results

available for the camera-ready version of the paper.

2 Related Work

Prior works related to our paper can be divided into three

broad categories.

Wikipedia. Since its constitution, Wikipedia attracted a

large number of researchers that contributed to tangible ad-

vancements leading to a quality improvement of the ency-

clopedia as reliable knowledge media. Over the years, the

community defined automated procedures to assist editors in

checking the veracity of references [Redi et al. 2019], sug-
gest uniform structure for articles of similar objects [Pic-
cardi et al. 2018] or looking for fake articles [Kumar, West,

and Leskovec 2016]. Many focused on investigating recur-

rent behavioral patterns of the users. Exploiting users’ logs,

[Singer et al. 2017] define a user taxonomy that categorizes

readers according to their information needs and behavior to

meet those needs. Researcher were able to explain why users
give up in seeking information [West and Leskovec 2012]

Scaria et al. 2014], using Wikispeedia data [West, Pineau,

and Precup 2009]. More recent analyses show that readers
tend to click links close to the top of the screen [Dim-
itrov et al. 2016]. Moreover, there is a model that com-

bines structural, semantic and visual features of hyperlinks
to understand and explain users’ next-link [Dimitrov et al.

2017]. In this paper, we exploit the findings of these works
to characterize the Markov Chain used for detecting the dy-
namic structural bias. Regarding the problem of bias, al-
though Wikipedia advocates a strict neutral point-of-view
policy, research showed the presence of cultural bias among

same articles in different languages [Callahan and Herring

2011] and highlighted differences between women and men

biographies [Graells-Garrido, Lalmas, and Menczer 2015]

Wagner et al. 2016]. These previous lines of research, that

focused on content-based analysis, call for the necessity of

investigating bias more deeply and we decide to do it ex-

ploiting network topology going beyond pages’ content.

Controversy on the Web. Researchers and companies have

been studying how to capture the controversies we observe

at the societal level on the Web. The ways to approach the

problem are mainly two. The first consists in text and senti-
mement analysis [Mejova et al. 2014; Dori-Hacohen and Allan

2015], the second uses graph topology. The latter revealed

the polarization of online political debates, characterized by

a low degree of interaction among different leaning blogs

and the Twitter political conversation graph [Adamic and

Glance 2005; Conover et al. 2011]. To measure polarization

on graph [Guerra et al. 2013] introduced a metric account-
ing for the extent to which nodes on the partitions’ bound-
aries point toward the opposing sides. Recently [Garimella

et al. 2018] carried out an extensive work that proposes a

new more holistic method to analyze the issue of contro-

versy on Twitter, presenting a measure which aims to cap-

ture how deeply two partitions are separated. In contrast
to these methods that focus on quantifying the distance be-
 tween partitions in static frameworks, given the well-known

intrinsic clustered nature of Wikipedia [Brandes et al. 2009]

Lizorkin, Medelyan, and Grineva 2009], we look at the

strength of connections among partitions by proposing two

metrics that capture the static and dynamic structural bias.

Reciprocity is the likelihood of vertices in a directed graph
to be mutually connected [Squartini et al. 2013]. The met-

ric plays a crucial role when talking about networks that
carry information where mutual links facilitate the trans-
portation process. Second, it helps to estimate the error introduced when a directed network is treated as undirected. If we think of users as the information the network carries, since we want to verify if Wikipedia topic-induced networks allow users to mutually move among opposing partitions, we adapt the metrics to be used for bias detection purposes. Concretely, we keep the idea of measuring mutual connection but we redefine the way to do so, Section 3.

3 Structural Bias

As we mentioned in Section 1, structural bias refers to Wikipedia’s bias resulting from its underlying hyperlink network. Previous approaches for quantifying the polarization on partitioned graphs used metrics that focus on capturing the distance among the partitions (Grimmella et al. 2018). Instead of considering just the separation between two communities, we compare how easy is for a user to move from a community A to a community B with the moving from B to A. Thus, even if a network, such as Wikipedia, has well-separatated communities, if users have the possibility and tendency to move freely from one community to the other then we consider the network as a low-bias one. For instance, in the induced network of Politics in the United States, our framework on structural bias measures and compares the likelihood of moving from the Republican to the Democratic community with the inverse one. Accordingly, we formalize the idea of measuring the mutual probability of jumping across bubbles, in a static and dynamic settings.

Assume that we have a weighted directed graph $G = (V, E)$, with $|V| = n$, whose set of vertices is partitioned to sets $V_I$, $V_J$, the union of the two communities related to a given topic and $V_{external}$, including nodes one-hop distant from each node in $V_I \cup V_J$. Let $P_I = (V_I, E_I)$ and $P_J = (V_J, E_J)$ be the induced subgraphs. We now formally define the two kinds of structural bias that we introduced in Section 1.

3.1 Static structural bias

The value of static structural bias tells us the amount of flow that is not shared between $P_I$ and $P_J$. In order to measure it, we provide a metric that exploits the idea of reciprocity (Squartini et al. 2013) and proposes a modification that makes it suitable for bias detection purposes over partitioned graphs. In particular, our method devalues the magnitude of the flow from $P_I$ to $P_J$ proportionally to the portion of nodes in $P_I$ having outgoing edges pointing to $P_J$.

Let $A = \{a_{ij}\} \in \{0, 1\}^{n \times n}$ be the adjacency matrix of $G$, with $a_{ij}$ denoting the weight of node $i$ to node $j$. The weights of $A$, $a_{ij}$ equal

- 1 if there is an edge from node $i$ to node $j$, otherwise 0 (uniform)

Matrix $A$ is transformed in a row stochastic matrix $H$ whose element $h_{ij} \in [0, 1]$ is the probability of going from node $i$ to node $j$.

Let $\pi_i = \{(\pi_i)_s\} \in \mathbb{R}^n$ be an array with $(\pi_i)_s = \frac{1}{|V_i|}$ if node $i$ belongs in $V_I$ and 0 otherwise. Then we denote by $f_{I \rightarrow J}$ the flow from partition $P_I$ to partition $P_J$ defined as

$$f_{I \rightarrow J} = \sum_{j \in V_J} \langle H \cdot \pi \rangle_j,$$

representing the sum of weights from nodes in $P_I$ to nodes in $P_J$, averaged by the cardinality of $P_I$. Put differently, it describes the strength of connection from partition $I$ to partition $J$.

A large flow $f_{I \rightarrow J}$ indicates that it is easy for a user to move from partition $P_I$ to $P_J$. To measure the bias we compare the flow from $P_I$ to $P_J$ with the one from $P_J$ to $P_I$. Therefore, we define the reciprocity $r_{I \rightarrow J}$ between $P_I$ and $P_J$ as

$$r_{I \rightarrow J} = \min \{f_{I \rightarrow J}, f_{J \rightarrow I}\} \max \{f_{I \rightarrow J}, f_{J \rightarrow I}\}.$$

Note that $r_{I \rightarrow J} = r_{J \rightarrow I}$. Finally, we define the static structural bias $b_{I \rightarrow J} = 1 - r_{I \rightarrow J}$, which represents the anti-reciprocated component between partition $I$ and $J$.

3.2 Dynamic structural bias

In the previous section, we provide a definition for bias that depends on the graph structure and is agnostic to how users navigate over the network. In this section, we take into account users’ navigation behavior, as described by Wikipedia’s clickstream log. We consider the following dynamic Markovian model. We collect the data over a time window of one month. Let $C_{ij}$ be the number of clicks from page $i$ to page $j$ and let $C_{i \perp}$ be the number of sessions (we define a session as a sequence of pages that a user visits by following links (Singer et al. 2017)) terminated on page $i$. Furthermore, let $s_i$ be the number of sessions that started in page $i$. We define the Markov chain, with $n + 1$ states, corresponding to the $n$ pages in $V$ and in addition an absorbing state $\perp$. We define the transition probability matrix $P = \{p_{ij}\} \in \{0, 1\}^{(n + 1) \times (n + 1)}$, where for each $i \in V$ and $j \in V \cup \{\perp\}$ we let

$$p_{ij} = \frac{C_{ij}}{\sum_i C_{ij}},$$

$p_{i \perp} = 1$, and for $j \in V$, $p_{i \perp} = 0$. To measure the ease to move from partition $P_I$ to partition $P_J$ we consider a user who starts at a random page and moves following the clickstream frequencies. We model this, by considering the Markov chain $X^t: t = 0, 1, \ldots$, induced by the transition matrix $P$ with starting state $X^0$ selected from the distribution $p_I = \{(\rho_i)_t\} \in \mathbb{R}^n$ over $V$, which assigns probability to node $i$ equal to $(\rho_i)_t = s_i \sum_i \ell \in V_i \sum_j s_j$ if $i \in V_I$, and $(\rho_i)_t = 0$ if $i \not\in V_I$.

Having defined the Markov chain that models users’ browsing behavior, we use it to define the structural bias for navigation sessions of different length in terms of clicks. We define the dynamic structural bias as $b'_{I \rightarrow J} = 1 - r'_{I \rightarrow J}$, where

$$r'_{I \rightarrow J} = \min \{f'_{I \rightarrow J}, f'_{J \rightarrow I}\} \max \{f'_{I \rightarrow J}, f'_{J \rightarrow I}\}.$$

Wikipedia makes public aggregate click information.
and
\[ f_{i \rightarrow j} = \sum_{j \in V_j} \Pr(X^t = j) = \sum_{j \in V_j} (\rho_i \cdot P^t)_j, \]
which approximates the probability for a typical user who starts in \( P_t \) to arrive at a page in \( P_j \) at step \( t \). We recall that the graphs we consider for the computations include external nodes, thus when quantifying flows we take into account navigation sessions in which users reach opposing knowledge bubble passing through external pages.

### 3.3 Null model

Whereas the aforementioned metric capture the bias when \( P_t \) and \( P_j \) are of comparable size, it may fail if one is much smaller than the other: if, for instance, \( P_t \) is 10 times larger than \( P_j \), then, if pages of both partitions have a similar outdegree distribution, one would expect \( f_{i \rightarrow j} \approx 10 \cdot f_{j \rightarrow i} \), and, as a result, \( r_{IJ} \approx 0.1 \) and \( b_{IJ} = 0.9 \).

To resolve this issue we consider a null model that serves as baseline in our experimental sections. It corresponds to the configuration random-graph model (Newman, Strogatz, and Watts 2001) which selects a graph uniformly at random among all graphs having the same in and out degree as in \( G \), preserving the in/out degrees of each node. This is a model typically used when dealing with community detection. In our framework, it allows us to compare the mutual connectivity among partitions in the real networks and the null model networks, that we assume to not suffer of bias, due to their random generative process. On this null graphs, we compute the reciprocity and bias values, \( r_{IJ}^{\text{NM}} \) and \( b_{IJ}^{\text{NM}} \). For the reminder of the paper, we use the terms null model and random graph interchangeably.

### 4 Data

We investigate the phenomenon of structural bias on several Wikipedia’s subgraphs induced by articles related to a set of given topics. The shape of topic-induced networks, thus the division in partitions, corresponds to the one described in Section 3. In the remainder of the section, we explain how we collect, preprocess, and characterize the graphs.

**Data collection.** The essential ingredient to assemble a topic-induced network is the topic itself. Once we choose it, we proceed as follows; refer to Figure 2 for more clarity.

1. We handcraft the category seeds, a list of Wikipedia’s categories, and respective labels, that gather topic related pages of opposing inclination.
2. We extract all the pages belonging to the category seeds and their respective subcategories, by making use of Wikipedia’s category API.
3. Throughout articles’ harvesting, we label pages with the respective category’s label.
4. We add all Wikipedia’s pages at one-hop distance to the set of collected articles, and we label them as external.
5. We connect pages with directed edges, indicating that that page \( i \) has a hyperlink pointing to page \( j \).

#### Figure 2: The flow chart explains the data collection process.

The articles’ underlying networks come from Wikipedia’s English dump of August 2019 and they only include ties among Wikipedia’s articles, known as wikilinks. The controversial topics are abortion, cannabis, guns, politics, religion, and sociology. Pages in the graphs relate to movements, people, campaigns, correlated events and topic explanations. Table 1 summarizes information about the networks and how they polarize. Because the data collection procedure does not depend on Wikipedia’s network, it does not affect our network analysis. A limitation of the data collection process is that the corpus we obtain may lack of pages not assigned by editors to topic’s categories. Despite this, past research already employed this method highlighting that, because of the articles’ review procedure, we expect pages’ labels to be reliable (Shi et al. 2019).

**Data preprocessing.** To preserve the accuracy of the analysis, we discard stubs and all pages not classifiable as articles (i.e., categories, meta-pages). If, throughout the data collection, a page is assigned to more than one partition, we assume that it expresses a neutral opinion, thus it is assigned to \( V_{\text{external}} \).

**Data characterization.** To run experiments, for each topic we refer to four different representation serving different purposes.

- **Uniform graph.** \( G_{\text{uniform}}^{\text{topic}} \), describes the topology of the network and its edges are uniformly weighted. We use it to measure the static structural bias and as a baseline to analyze users’ behavior capturing the scenario in which users click any link in the page with the same probability.
- **Order graph.** \( G_{\text{order}}^{\text{topic}} \), has edges weighted according to the link’s position in the page. With this graph, we capture the scenario in which users click with higher probabilities links positioned on the top of article’s body (Dimitrov et al. 2017).
- **Clickstream graph.** \( G_{\text{clickstream}}^{\text{topic}} \), depicts the graph really explored by users. Its edges’ weights are the number of page requests extracted from the server log, in August 2019, in the form of \((\text{referer}, \text{resource})\) (Wulczyn and Taraborelli 2017). These numbers reflect the flow of users who move clicking each link. If a hyperlink has fewer than \( \theta = 10 \) clicks it does not appear in the log. Since
the those rarely clicked links exist, we apply a smoothing factor equal to $\theta$ to include the chance of clicking them. We use this graph to study users’ exposure to structural bias over the course of navigation sessions.

- Random graph, $G_{\text{random}}^{\text{topic}}$, is generated from a configuration random model (Section 3.3). The edges’ weights are uniform. When computing the dynamic structural bias, this graph is adopted as a baseline since it allows us to consider the intrinsic network’s bias coming from the disparity of graph’s partitions size (Newman, Strogatz, and Watts 2001).

Because we are interested in understanding users’ behavior on the networks, when studying the dynamic structural bias, as described in Section 3.2, we assign to each page the entry probability of quitting the session in our models, we add an absorbing state $\perp$ that users get to the absorbing state $\perp$, introduced in 3.2. Consideration about collected data. The list of topics we pick includes those that researchers investigate when talking about bias on the Web. In Table 1, we observe that the size of the opposing partitions, knowledge bubble, is unbalanced. We hold to be true that the different size of partitions represent the intrinsic bias of the network that, most of the cases, is irreducible. For instance, we consider the topic abortion. The anti-abortion movement looks more represented than the abortion-rights one. It means that a user who randomly picks a Wikipedia’s page, has double the probability of reading an article related to anti-abortion than abortion rights. In fact, it is undeniable that one perspective of a topic may deliver more content, implying a higher number of articles on Wikipedia. Nonetheless, it is worth to mention the possibility that the intrinsic bias may depend on editors supporting different opinions thus interested in writing about one of the two positions (Shi et al. 2019).

Table 1: The table presents the category seeds for each topic and information about the respective topic-induced subgraphs. The last two columns show the percentage of edges that from a partition point to the opposing.

| topic               | partitions         | category seeds         | #nodes | #partitions | #edges | % edges $I \rightarrow J$ | % edges $J \rightarrow I$ |
|---------------------|--------------------|------------------------|--------|-------------|--------|--------------------------|---------------------------|
| abortion            | anti-abortion (I)  | anti-abortion movement | 22.5k  | 291         | 570k   | 12.38                    | 14.87                     |
| abortion rights (J) | abortion rights movement |                        | 21.8k  | 281         |         |                          |                          |
| cannabis            | pro-cannabis (J)   | cannabis activism      | 13.5k  | 48          | 315k   | 1.17                     | 17.39                     |
|                     | anti-cannabis (J)  | cannabis prohibition   |        |             |        |                          |                          |
| politics            | republican (J)     | republican party (United States), republicans (United States) | 217.3k | 10.3k       | 6.5M   | 23.88                    | 24.10                     |
|                     | democratic (I)     | democratic party (United States) |        |             |        |                          |                          |
| religion            | judaism (J)        | judaism                | 286.6k | 21.4k       | 7.5M   | 2.68                     | 6.39                      |
|                     | islam (I)          | islam                  |         |             |        |                          |                          |
| sociology           | individualism (J)  | individualism          | 99.8k  | 900         | 2.6M   | 2.27                     | 9.97                      |
|                     | collective (I)     | collective activity     |        |             |        |                          |                          |
|                     | external           |                        |        |             |        |                          |                          |

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5 WikiNetBias

In this section, we investigate the presence of structural bias on the set of collected topic-induced networks. The analysis addresses five main research questions that guide the reader throughout the exploration of the problem of structural bias. RQ1. What is the structural bias of the network? Does its topology potentially channel users towards a specific opinion?

RQ2. What is the dynamic structural bias of the network? Over the course of a navigation session, what is the structural bias users are exposed to?
5.1 RQ1: Static Structural Bias

To discover network’s skewness toward a specific viewpoint we evaluate the static bias, Section 3.1, on $e_{\text{uniform}}$. In Figure 3, we plot the flows going to and coming from each partition of the graphs $(f_{J \rightarrow I})$. The graph is biased toward the partition having the highest entry flow. The non-overlapping portion, anti-reciprocated component, of flows represents the static structural bias. The bigger it is, the more the bias is.

All the networks present an anti-reciprocated component greater than 0, that makes them structurally biased. Except for religion and guns, we notice that on networks of unbalanced partitions, it is easier to reach pages belonging to the smallest partition. For instance, a user reading about cannabis activism has more than four times the probabilities of reading about cannabis prohibition than the opposite. In contrast, for guns, even if the size of the gun rights bubble is bigger than the gun control bubble, we observe that hyperlinks’ placement gives users reading about less opportunities of reading about guns control than gun rights. In general, topic-sides with high out-going flows underline that editors mention more frequently the contrasting view or better diversify links’ placement in pages. The topics reporting the lower gap between flows are politics and abortion. The two are mainstream themes whose tendency to polarize on the Web, during the last years, has been abundantly discussed. For this reason we can imagine a strong community’s commitment for balancing the connections among opposing factions. For topics as guns, abortion and cannabis, conservative inclination bubbles give users less chances of reading about the contrasting opinion.

5.2 RQ2: Dynamic Structural Bias

In this section we aim to understand how users’ traverse Wikipedia’s controversial topics, thus the level of dynamic bias they face. Figure 4 illustrates how users’ exposure to bias changes over the course of a navigation session.

The trends referring to the clickstream graph, for all the topics, but cannabis and sociology, show that the dynamic structural bias turns out to be greater than the expected on the baseline models, even on the long run. In other words, users tend to navigate pages belonging to the same partition. On the other hand, users reading about cannabis and sociology have more chances than expected to jump between the partitions overcoming the intrinsic bias coming from graphs’ topological limitations. In fact, for topic like sociology we would not expect a strong polarization of users toward any of the two sides.

The dynamic structural bias for clickstream models shows a recurrent pattern consisting of a drop of the structural bias for the first few clicks and a sequential increment when the navigation session gets longer. This behavior suggests that users tend to start sessions on pages linking to articles of diverse inclinations. We can explain this by more in-depth investigations. In fact, the pages’ entry probabilities is positively correlated with pages’ centrality ($\sim$0.9) and hyperlinks diversification ($\sim$0.8). Thus, during the first clicks of a session, the exposure to the partitions gets more symmetric. One can think that initially users jump among pages of different partitions. Then, after 6-7 steps the dynamic structural bias increases and users have higher probabilities of following links that conduct to pages inside one of the knowledge bubbles, that do not point to contrasting viewpoint articles, likely more peripheral pages. Summarizing, one can imagine that users first click around to explore the topic and then focus on one perspective for more in-depth researches.

5.3 RQ3: Opposing bubble hitting time

To see how quickly a user can exit from a knowledge bubble, we compute the probability that after $X - 1$ consecutive clicks in the same bubble, users hit the opposite one. Figure 5. For all the topics, but politics, with respect to expected users’ behaviour on the random graph, that only suffers of intrinsic bias due to partitions’ size, real users require more steps to reach pages of opposing inclination. Referring to abortion, users on the random graph have probability 1 of reaching the opposing side after 5 clicks. Instead, the number of pages Wikipedia’s users need to read before getting to the opposing partition is 8, for those that start their session from the abortion rights knowledge bubble, and 10 for users starting from the anti-abortion bubble. Other than differences between curves related to the random and clickstream graphs, all the topics, but politics, show a delay in the number of clicks users need to move from bubbles representing progressive opinions, to those expressing more conservative viewpoints. At first sight, this finding looks in contrast to what we observed in 5.1 where progressive bubbles...
In this section, we want to know if, starting a navigation session, the presence of structural bias on the topic-induced networks.

Exploring the previous research questions, we assess the probability of reaching knowledge bubbles is the same. We find on Wikipedia. For instance, the ratio on the random graph represents the bubble's size unbalance. Referring to the real users behaviour (clickstream), in the case of abortion, short sessions correspond to higher probability of reaching the bubble about abortion rights. Accordingly to results of RQ1 and RQ2, the network is biased toward the anti-abortion bubble so, after more steps, thus for longer sessions, the probability of ending up on articles about the abortion rights movement is lower. For politics, when navigation sessions are short, there is a distortion toward the democratic bubble that mirrors the random instance. Instead, when the session becomes longer, the probability of reading a republican article gets larger than that of reading democratic pages. For the remaining topics, longer the sessions are more difficult is to reach one of the two bubbles.

5.5 RQ5: Reciprocity on multi-topic networks

To address RQ5, we separately join the politics-induced network with abortion, guns and sociology. In Figure 6, we sketch the graph obtained by joining two networks. The aim of the analysis is to verify whether bias present at societal level, is the same we find on Wikipedia. For instance, is the democratic bubble sharing stronger mutual-references with point to conservative bubbles with more strength. Actually, if we dig into the graph topology, we see that the density of hyperlinks among progressive articles is higher than that in conservative bubbles. This explain the fact that users need to read more consecutive pages in bubble presenting progressive inclinations before reaching pages of contrasting opinions. Fortunately, if we consider the topic politics the clicks users need to exit from the Republican or Democratic bubbles is the same.

The probabilities computation rely on the model presented in Section 5.2 using as adjacency matrices those corresponding to the clickstream and null model networks. The adjacency matrices are modified such that when sessions start from nodes in \( V_I \) each of the nodes in \( V_J \) becomes an absorbing state by adding a self-edge with weight 1. In this way, we are able to estimate the probability of hitting the opposite bubble at each step. It is important that while analyzing these results we keep in mind that at each step (click) of the navigation session the probabilities are computed over a diminishing number of users. Recently, Piccardi et al. 2020 show that after the first page the 50% of users continues its navigation. Unfortunately, given the aggregated data, we can not provide information about the exact lengths of sessions that we reasonably estimate.

5.4 RQ4: Probability of reaching knowledge bubbles from external pages

Exploring the previous research questions, we assess the presence of structural bias on the topic-induced networks. In this section, we want to know if, starting a navigation session reading an article belonging to the external partition of the graph, the chances of reaching pages belonging to the two different knowledge bubbles is the same. To do that, we study the flows going from \( V_{external} \) to the two knowledge bubbles, again exploiting models used in Section 5.2. In Figure 7, we plot \( Pr(V_{external} \rightarrow P_J) \) that indicates whether the strength of going from external nodes to the two knowledge bubbles is balanced. The value of the ratio on the random graph represents the bubble's size unbalance. Referring to the real users behaviour (clickstream), in the case of abortion, short sessions correspond to higher probability of reaching the bubble about abortion rights. Accordingly to results of RQ1 and RQ2, the network is biased toward the anti-abortion bubble so, after more steps, thus for longer sessions, the probability of ending up on articles about the abortion rights movement is lower. For politics, when navigation sessions are short, there is a distortion toward the democratic bubble that mirrors the random instance. Instead, when the session becomes longer, the probability of reading a republican article gets larger than that of reading democratic pages. For the remaining topics, longer the sessions are more difficult is to reach one of the two bubbles.

Figure 4: Dynamic structural bias: The plots indicate the level of structural bias of each topic-induced network for navigation sessions of different length. For each subject we display four lines corresponding to measurements on the uniform graph (squares and purple line), order graph (triangle and orange line), clickstream graph (circles and green line) and random graph (crosses and red line). Lines above the random graph line detect the presence of structural bias coming from the hyperlinks structure other than the intrinsic bias. Lines below show that the topology of the graph overcomes the intrinsic bias. The measurements on the random graph are computed 100 times and we report the 95% confidence intervals, so small that do not show up.
Figure 5: Probability of hitting the opposite side after X consecutive clicks in the starting bubble. The plots show the probability that users reach the opposite bubble after reading X-1 articles in the partition where they started their session. The dashed lines represent the probabilities of random users walking on the random graph. The areas under the continuous curves describe the probabilities of real users. The more the curves are skewed to the right, more clicks users need to get out of a bubble. When the areas under the curves overlaps users exit from the bubbles with the same speed (number of clicks).

Figure 6: The figure sketch a multi-topic network. In this example we represent the union of politics and abortion induced networks. The image does not show the external partition, but it is in the graph.

6 Discussion and Conclusions

Our work gives three main contributions. First, we shed light on the problem of bias on Wikipedia from a perspective that does not focus on articles’ content, but rather investigates bias coming from the structure of the network underlying the encyclopedia. To our best knowledge, this is the first time the problem of bias on Wikipedia is tackled with a graph-based approach. Second, we build new tools to measure structural bias on Wikipedia (Section 3), with a specific focus on understanding if the way users explore the network is somehow affected by structural bias (Section 3.2 and 5). Finally, we collect topic-induced networks for several controversial topics (Section 4).

The analysis we run provides important insights regarding the presence of structural bias on a group of Wikipedia’s topic-induced networks and suggest the following:

- Most, if not all of the controversial topics present structural bias. In Section 5.1, we show that for all the topics that we studied, the chances of moving between contrasting knowledge bubbles differ and are greater than expected.
- The networks explored by real users point out higher structural bias than expected. The walks of real users turn out to be very biased. Certainly, confirmation bias is a cause of this phenomenon, as users’ personal bias leads them to remain in their bubble, yet the presence even of what we call static structural bias exacerbates the phenomenon. (Section 5.2).
- Longer navigation sessions expose users to higher level of structural bias. Users who seek information on Wikipedia, by sequentially clicking a few hyperlinks to explore the network get progressively less exposed to articles of divergent inclination (Section 5.2).
- Users starting their session from pages of conservative opinions, exit from their bubble in fewer clicks than those reading about progressive viewpoints. It means that progressive bubbles’ users retention is higher than the conservative ones (Section 5.3).
- In the long run, users starting the exploration from pages external to the knowledge bubbles have a higher likelihood of reaching articles belonging to the bubble towards which the network is skewed. It means that structural bias measured between the knowledge bubbles also has an effect on navigation sessions of users reading pages that do not belong to knowledge bubbles (Section 5.4).
The reciprocity relationship between politics knowledge bubbles and abortion and guns topics reflect the proximity observed at societal level. Pages belonging to republican and democratic bubbles direct users towards a narrow set of opinions. If Wikipedia wishes to offer unbiased information, it needs to fix this problem (Section 5.5).

The limitations of our work lie mainly in the graph construction. To collect and label topics’ pages we handcrafted the list of categories of interest. At first glance, this procedure may sound unsophisticated as it is not automated. Because this work is the first that aims to quantify structural bias, we preferred to have total control on the choice of categories and articles to analyze. This paper leaves rooms open for future works that:

- Define a more general framework to automatically detect the graph’s partitions employing community detection algorithms.
- Explore more topics not necessarily controversial or limited to two partitions.
- Expand the time window of clickstream analysis, that we restrict to one month to be consistent with the Wikipedia’s dump from which we extracted data.
- Compare the level of structural bias of topic-induced networks across languages.
- Build a system that helps editors distributing hyperlinks on pages to minimize the bias.

In the light of the above findings and limitations, and considering the enormous amount of users who access Wikipedia daily, we deem the problem of studying structural bias to be crucial and worth to be further explored with the goal of both overcome the constraints of methodologies we used, and propose algorithms that help out the community to mitigate the presence of the phenomenon. We believe that enabling Wikipedia’s users to expose themselves to opposing opinions, means to give people the possibility of being able and free to make deliberate choices.

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Table 2: Reciprocity among bubbles of multi-topic networks. The couples of topics are: politics vs. abortion, politics vs. guns and politics vs. sociology. Greater the reciprocity is, higher the chances that users read about both bubbles.

| bubbles    | kind   | abortion rights | anti-abortion | gun rights | gun control | individualism | collectivism |
|------------|--------|----------------|---------------|------------|-------------|---------------|--------------|
| republicans| random | 0.85           | 0.88          | 0.93       | 0.90        | 0.55          | 0.61         |
|            | order  | 0.79           | 0.79          | 0.81       | 0.78        | 0.46          | 0.59         |
|            | clickstream | 0.42    | 0.55          | 0.60       | 0.49        | 0.78          | 0.86         |
| democratic | random | 0.90           | 0.84          | 0.89       | 0.94        | 0.40          | 0.65         |
|            | order  | 0.87           | 0.75          | 0.72       | 0.84        | 0.41          | 0.68         |
|            | clickstream | 0.78   | 0.33          | 0.37       | 0.82        | 0.74          | 0.80         |

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