Novel version of PageRank, CheiRank and 2DRank for Wikipedia in Multilingual Network using Social Impact

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Abstract. Nowadays, information describing navigation behaviour of internet users are used in several fields, e-commerce, economy, sociology and data science. Such information can be extracted from different knowledge bases, including business-oriented ones. In this paper, we propose a new model for the PageRank, CheiRank and 2DRank algorithm based on the use of clickstream and pageviews data in the google matrix construction. We used data from Wikipedia and analysed links between over 20 million articles from 11 language editions. We extracted over 1.4 billion source-destination pairs of articles from SQL dumps and more than 700 million pairs from XML dumps. Additionally, we unified the pairs based on the analysis of redirect pages and removed all duplicates. Moreover, we also created a bigger network of Wikipedia articles based on all considered language versions and obtained multilingual measures. Based on real data, we discussed the difference between standard PageRank, Cheirank, 2DRank and measures obtained based on our approach in separate languages and multilingual network of Wikipedia.

Keywords: PageRank · Wikipedia · CheiRank · Clickstream · Pageviews · Google Matrix · Centrality Measures

1 Introduction

For the last 10 years, Wikipedia has been one of the most popular source of knowledge. In different countries, this online encyclopedia is in the top 10 most visited websites [1]. Wikipedia even influences the language used by scientists in their publications [33]. Nowadays, this free encyclopedia contains over 51 million articles in more than 300 languages [36]. Content on a separate subject can be created and edited independently in each language version of Wikipedia [26]. Often a Wikipedia article contains links to other pages, which can be used to find more information related to the subject. Based on links between articles,
it is possible to identify important places, persons, products in specific area or language community. To find such important Wikipedia articles, different methods can be used. One of the well-known algorithms for this purpose is PageRank [30].

The google matrix and the PageRank algorithm are at the foundation of the very famous search browser Google [2]. They describe a random internet user, surfing on the World Wide Web (WWW). Indeed WWW can be seen as a directed network where nodes are Web pages and links are hyperlinks allowing an internet user to navigate. By knowing a network’s topology we can construct its adjacency matrix \( A \) as well as its stochastic matrix \( S \). Its mathematical aspect is well described in [24]. Centrality measures in complex network theory are important, especially as nowadays networks are very large and complex (high occurrence of nodes and links). In case of directed networks such as WWW, eigenvector-based centrality measure is helpful and efficient as demonstrated by Google’s web search engine. However, this simple random walk model may be limited for describing a human user’s behaviour. PageRank algorithm, applied to the Wikipedia network, leads to robust ranking lists of articles and articles of countries tend to be well ranked. Using a simple random walk, such algorithm didn’t allow us to observe a trend of interest from readers.

In this study, we extend the usual PageRank algorithm with clickstream’s and pageview’s data from Wikipedia October 2019’s dumps. In this paper, we first mention works related to Wikipedia and PageRank algorithm, then we present you the “WikiClick” (\( wc \)) and “WikiClick Plus View” (\( wcpv \)) models and finally we discuss how this social information affects Wikipedia articles ranking.

2 Related works

Pageviews statistics in Wikipedia [11] can show which article is popular over a specific period. Therefore, we can observe a topic trend over time. Using such data, it is possible to forecast stock market moves [29], movies’ success [28, 25], demand for services in the tourism sector [21], cryptocurrencies price and market performance [22, 27], epidemics in specified territory [20] and can be used in electoral prediction [37]. Moreover, it can be used to assess the quality of Wikipedia articles alongside other measures (such as text length, number of references, images, sections and others) [24, 29].

Google matrix and PageRank algorithm have been applied to Wikipedia for ranking articles related to historical figures [13] and Universities [23]. We can also find studies on the World influence for Universities [4], cancers [31] and infectious diseases [32] using the Wikipedia network. The Wikipedia articles ranking evolution over time using PageRank and CheiRank for countries, historical figures, physicist and chess players have been investigated in [15]. Spectral analysis of the Google matrix permits us to retrieve communities of articles [17]. Moreover the google matrix analysis have been used in business oriented networks such as the World trade network [5] and cryptocurrencies network [3].
The use of the internet users’ behaviour information such as pageviews and clickstream data has been studied for the biomedical ontology repository BioPortal [18]. Pageviews data is used by pantheon group to rank famous individuals from Wikipedia [38]. Clickstream data has been used to study the navigational phase space of Wikipedia [19].

3 Proposed methods

3.1 Wikinetwork models

In such network, nodes are Wikipedia articles and the directed link $A \rightarrow B$ exists if article $B$ is reachable from article $A$ by using an intra-wiki hyperlink. Usually, we consider the unity rule for such links, it means that we count once such hyperlink in article $A$. It follows that the corresponding adjacency matrix will be asymmetric and its elements are equal to $1$ or $0$. We call this model the standard wikinetwork model (nowc).

Information from wikidata such as clickstream for intra-wiki hyperlinks provides an interesting social bias of the Wikipedia network. We construct two different models of Wikipedia network: wikiclick (wc) and wikiclick plus view (wcpv). We compare results obtained using these methods with nowc.

3.2 Google matrix and Ranking algorithms

**Google matrix** The google matrix $G$ is a Perron-Frobenius operator based on the stochastic matrix of a network and a teleportation term. We detail here the construction of $G$ for each model.

The general formula for the google matrix is

$$G = \alpha S + (1 - \alpha)fe^T$$

where $\alpha$ is the so-called damping factor, $S$ the stochastic matrix, $e^T$ a row vector with $N$ ones and $v$ is a preferential vector such as $\sum_j v_j = 1$. $\alpha = 0.85$ is a standard value for different real complex networks, such as WWW.

The teleportation term $ve^T$ may simply be a matrix of elements equal to $1/N$.

The google matrix for the standard model is computed with this trivial teleportation term.

$S$ is computed from the adjacency matrix describing the network topology

$$A_{ij} = \begin{cases} 1 & \text{if edge } j \rightarrow i \text{ exists} \\ 0 & \text{else} \end{cases}$$

In case of wc version of Wikipedia network, we simply use $W$ the matrix of clicks where $W_{ij}$ element is the number of clicks received, article $i$ from article $j$. The Wikidata for clickstream only counts clicks $\geq 10$, $W_{ij} = 0$, therefore elements are replaced by a standard $A_{ij}$ element representing the possibility of
click because the link exist in the network, this final weighted adjacency matrix is noted $A_{wc}$. From $A_{wc}$, we define the stochastic matrix $S_{wc}$ representing the probability to reach node $i$ from $j$ by:

$$S_{wc_{ij}} = \begin{cases} \frac{A_{wc_{ij}}}{\sum_{i'} A_{wc_{i'j}}} & \text{if } \sum_{i'} A_{wc_{i'j}} \neq 0 \\ \frac{1}{N} & \text{if } \sum_{i'} A_{wc_{i'j}} = 0 \end{cases}$$

(3)

We also use pageviews information as a teleportation matrix instead of $v^T$. In that way, the preferential vector component $v_j = \#\text{views for article } j$. $\tilde{v}$ is the normalized vector computed from $v$ such as $\sum_j \tilde{v}_j = 1$.

Finally, we obtain:

$$G_{ij} = \begin{cases} \alpha S_{wc_{ij}} + (1 - \alpha)/N & \text{for } wc \\ \alpha S_{wc_{ij}} + (1 - \alpha)\tilde{v}_i & \text{for } wc_{pv} \end{cases}$$

(4)

**PageRank and CheiRank algorithm** The leading right eigenvector of $G$ with corresponding eigenvalue $\lambda = 1$ corresponds to the steady state of a random walker moving through the network for an infinite time. We have the relation

$$GP = P$$

(5)

where $P$ is called PageRank vector, its $i^{th}$ component represents the probability that a random surfer reaches node $i$ after an infinite journey. By sorting components in decreasing order, we obtain the nodes ranking. PageRank measures ingoing links efficiency, seen as importance ranking. Let $K_1, K_2, ..., K_N$ be the PageRanks of the nodes such as $P_{K_1} > P_{K_2} > P_{K_3}$ and so on.

To measure the efficiency of outgoing links, we simply reverse the direction of all the network’s links. This leads to a new adjacency matrix $A^*_{wc} = A^T_{wc}$ and then we compute the corresponding google matrix noted $G^*$.

CheiRank vector ($P^*$) is defined as the eigenvector of $G^*$ such as $G^* P^* = P^*$ and note $K^*_1, K^*_2, ..., K^*_N$ the obtained ranking of nodes.

**2DRank algorithm** PageRank and CheiRank algorithms are two sides of the same coin, the first one describes relevance of an article within Wikipedia’s network and the last one represents its communicability. As described in [39][16], we can place nodes of a network in the two-dimensional $(K, K^*)$ plane. The 2DRank algorithm uses both rankings and is defined as following:

- Firstly, for each node let, $K_{max}(i) = \text{Max}(K_i, K^*_i)$.
- Secondly, we sort nodes in ascending order according to their $K_{max}$.
- Finally, we sort couple of nodes with the same $K_{max}$ regarding the increasing $K^*$ ordering.
4 Datasets and extraction methods

To extract data about links between Wikipedia articles (wikilinks or intra-wiki), we use Wikipedia dumps from October of 2019 [34]. We focused on two separate approaches to identify these links:

- **XML** - directly from the Wikicode [10] (XML dumps)
- **SQL** - rendered versions of the articles (SQL dumps).

In the case of Wikicode, for each article, we searched internal links (wikilinks) [8] placed in doubled square brackets in code for each considered language version (below example for English Wikipedia):

- "enwiki-20191001-pages-articles.xml.bz2" - recombined articles, templates, media/file descriptions, and primary meta-pages.
- "enwiki-20191001-redirect.sql.gz" - redirect list.

Among the extracted links were also the ones that led to other types of Wikipedia pages (other namespaces [9]). Therefore, we only kept those belonging to article namespace (ns 0). We also removed links leading to nonexistent articles (so called "red links" [12]). Additionally, we took into account other names of the same articles based on redirects [13].

Rendered version of the articles usually have more links to other pages than we can find in their source (in Wikicode). It comes from additional elements placed in the article. For example, we can find the same template with certain set of links in articles related to similar topic (such as French cities, cryptocurrencies, processors, Nobel Prize laureates and others). In order to analyze links in rendered version of the Wikipedia articles, we took into account other dumps files for each language version (below is an example for the English Wikipedia):

- "enwiki-20191001-pagelinks.sql.gz" - wiki page-to-page link records.
- "enwiki-20191001-page.sql.gz" - base per-page data (id, title, old restrictions, etc).
- "enwiki-20191001-redirect.sql.gz" - redirect list.

The table [4] shows statistics of the extraction source-destination pairs of links for each considered language version of Wikipedia. We extracted over 1 billion pairs from the SQL dump and over 500 million pairs from XML dumps. For every pair, we only took Wikipedia articles from ns 0. After excluding duplicate pairs, redlinks (nonexistent pages) and unification of the articles names (based on redirects), the total pair number is reduced.

For both methods we additionally extracted pageviews statistics [11] and clickstream data [35] (click counts of source-destination pairs of articles) from September 2019.

5 Application of Methods and Discussion

In this section, we detail the application of our method using different dumps of Wikipedia from October 2019. We have built the network from English edition
Table 1. All and unified source-destination pairs of links from Wikipedia in different languages. Source: own calculations based on Wikimedia dumps in October 2019

of Wikipedia from XML and SQL dumps as well as a multilingual version of the network. In the multilingual network, we took all language editions with available clickstream and pageviews data.

5.1 English edition

XML dumps. Table 2 shows the top 10 articles using \textit{wcpv} method and PageRank algorithm. For each of these articles, we also show its rank among $K_{wc}$, $K_{nowc}$, clickstream ($K_{cR}$) and pageviews ranking lists ($K_{vR}$).

We found articles related to sovereign states for \textit{wcpv} method, which is usually the case for \textit{nowc} PageRank. By comparing the top 10 from $K_{wcpv}$ with $K_{nowc}$ we see that this set of articles is a reordering of $K_{nowc}$ except for "Wikipedia", "List of Queen of the South episodes" and "Queen of the South (TV series)". These three articles are badly ranked in $K_{nowc}$ as well as in $K_{wc}$. The two first elements are well ranked because of their Pageviews. The third one is very interesting because "Queen of the South (TV series)" is badly ranked in all other ranking list. According to our method, we found a top 10 PageRank containing two articles related to the same TV series. This last result is not common for Wikipedia PageRank.

| Name                                          | $K_{wcpv}$ | $K_{wc}$ | $K_{nowc}$ | $K_{cR}$ | $K_{vR}$ |
|-----------------------------------------------|------------|----------|------------|----------|----------|
| United States                                 | 1          | 1        | 15         | 24       |          |
| Wikipedia                                     | 2          | 11665    | 3542       | 23014    | 1        |
| List of Queen of the South episodes           | 3          | 5170889  | 5128933    | 445536   | 2        |
| United Kingdom                                | 4          | 9        | 5          | 81       | 63       |
| New York City                                 | 5          | 23       | 19         | 150      | 139      |
| World War II                                  | 6          | 12       | 3          | 181      | 78       |
| Germany                                       | 7          | 7        | 4          | 142      | 113      |
| India                                         | 8          | 10       | 9          | 138      | 68       |
| France                                        | 9          | 5        | 2          | 1432     | 197      |
| Queen of the South (TV series)                | 10         | 166342   | 744237     | 28297    | 5871     |

Table 2. First 10 articles obtained by PageRank with \textit{wcpv} model from English Wikipedia. Source: own calculations based on Wikimeda dumps in October 2019.
The top 10 articles from CheiRank according to \( \text{wcpv} \) method is detailed in table 3. Usually, using the CheiRank method applied to Wikipedia network, articles related to a list of articles have a better rank than others. We do not see that in \( \text{wcpv} \). Indeed, we only have 4 lists ("Deaths in 2019", "2019 in film" and "List of Bollywood films of 2019") whereas \( \text{nowc} \) shows 100% of lists in its top 10. In the other articles of top 10 \( \text{wcpv} \) CheiRank, some are related to social interest such as "Joker (2019 film)" and "2019 FIBA Basketball World Cup". \( \text{wcpv} \) CheiRank is similar to \( \text{wc} \). We think that with the use of clickstream and pageviews, CheiRank algorithm gives us a list of entry points of Wikipedia.

| Name                                      | \( \text{K}_{\text{wcpv}}^* \) | \( \text{K}_{\text{wc}}^* \) | \( \text{K}_{\text{nowc}}^* \) | \( \text{K}_{\text{CR}} \) | \( \text{K}_{vR} \) |
|-------------------------------------------|--------------------------------|------------------|------------------|------------------|------------------|
| Deaths in 2019                            | 1                              | 2                | 909              | 406              | 4                |
| Lists of deaths by year                   | 2                              | 1                | 10               | 555939           | 7874             |
| It Chapter Two                            | 3                              | 10               | 334575           | 2                | 12               |
| 2019 in film                              | 4                              | 9                | 382              | 365              | 34               |
| List of Bollywood films of 2019           | 5                              | 12               | 19249            | 640              | 54               |
| Wikipedia                                  | 6                              | 421              | 11031            | 25013            | 1                |
| It (2017 film)                            | 7                              | 19               | 106231           | 18               | 37               |
| Joker (2019 film)                         | 8                              | 20               | 95165            | 33               | 10               |
| Mindhunter (TV series)                    | 9                              | 17               | 310462           | 147              | 35               |
| 2019 FIBA Basketball World Cup            | 10                             | 11               | 20498            | 44               | 13               |

Table 3. First 10 articles obtained by CheiRank with \( \text{wcpv} \) model from English Wikipedia. Source: own calculations based on Wikimedia dumps in October 2019.

In order to quantify changes in ranking of Wikipedia articles, coming from the used model, we computed two overlap measures \( \eta_N \) and \( \eta_O \). The first one measures the presence of same articles in two ranking lists and \( \eta_O \) measures the exact rank similarity. Quantitatively, by regarding fig. differences between rankings are related to rank switching rather than exact similarity. As we can see \( \eta_N \) is higher than \( \eta_O \) (inset plots). Moreover, at short range \( j \in [1, 20] \), we have the highest overlap measures, with \( \eta_N = 0.75(K_{\text{nowc}} \text{ vs. } K_{\text{wc}}) \), \( 0.7(K_{\text{nowc}} \text{ vs. } K_{\text{wcpv}}) \) for \( j = 20 \). In case of CheiRank overlap, we respectively have \( \eta_N = 0.35 \) and \( \eta_N = 0.15 \) comparing \( K_{\text{wc}}^* \) and \( K_{\text{wcpv}}^* \) with \( K_{\text{nowc}}^* \). Social information seems to change more drastically CheiRank than PageRank. When comparing \( \text{wcpv} \) and \( \text{wc} \) methods, we have an overlapping very close regarding both PageRank and CheiRank. The highest value for \( j = 100 \) is for \( K_{\text{nowc}} \text{ vs. } K_{\text{wc}} \) with \( \eta_N = 0.75 \). \( \text{wcpv} \) method gives us more differences in the top 100 with respectively 53% and 6% of similarity for PageRank and CheiRank algorithm. Exact overlap \( \eta_O \) is very low with 5% and 2% regarding \( K_{\text{wcpv}} \) and \( K_{\text{wc}} \) with \( K_{\text{nowc}} \) for \( j = 100 \). Exact similarity regarding CheiRank is 0.0 for \( \text{uc, wcpv and nowc} \) methods. The left panel shows us how similar \( K_{\text{wc}} \) (Resp. \( K_{\text{wc}}^* \)) and \( K_{\text{wcpv}} \) (Resp. \( K_{\text{wcpv}}^* \)) are, with clickstreams and pageviews statistical rankings. Highest measures are for CheiRanks, \( \text{wcpv} \) method has the highest overlap with \( vR \) (0.5 and 0.24) for both PageRank and CheiRank.
The overlap measures show us that when we take into account social impact in PageRank and CheiRank algorithm, we have a drastic change in the final ranking. This change is mainly due to pageviews information. We are interested in $wcpv$ method, because it brings new elements to both PageRank and CheiRank.

**Fig. 1.** Overlap $\eta_N$ versus rank $j$ for doublet of ranking lists computed from $wc$, $wcpv$ and $nowc$ models (left panels), from $wc$, $wcpv$, $cR$ and $vR$ (right panels) considering English edition. Inset plots correspond to exact overlap $\eta_O$. Solid and dotted lines are for PageRanks and CheiRanks.

Fig. 2 shows the distribution of articles in the $(K,K^*)$ plane. In case of $nowc$, articles with good PageRank have bad CheiRank and reversely. The $nowc$ method doesn’t represent the social interest and is robust with time. In case of both $wc$ and $wcpv$ methods, the articles in $(K,K^*)$ plane related to top $cR$ and $vR$ have a lower $K$ and $K^*$ value. As we can see with bottom panel, $wcpv$ method brings the top 100 of $vR$ and $cR$ at the left bottom corner of $(K,K^*)$ plane. Also the articles are much more along the diagonal. We think that using a nontrivial matrix teleportation, $wcpv$ method tends to give a PageRank and a CheiRank for an article that are much more similar compared to previous methods.

2Drank algorithm, based on both $K$ and $K^*$, gives a higher rank to an article that is central in term of incoming and outgoing links. In case of $wcpv$ method applied on English edition of Wikipedia, the top 10 contains only one sovereign country, which is "United States". The first element is "Wikipedia", which is expected, but also missing from $nowc$ 2Drank’s top 10 (478th). The top 10 of $wcpv$ 2Drank is far from the $nowc$ and $wc$ ones but closer to top $vR$. Articles of social interests present in this top 10 are "September 11 attacks", "Donald Trump", "Greta Thumberg" and "It Chapter Two".
Fig. 2. Density distribution of Wikipedia articles $W(K, K^*) = dn/dKdK^*$ in case of
nowc (bottom left), wc (top left) and wcpv (right) models. We have divided $K, K^*$
plane into $200 \times 200$ decimal logarithmic cells. For each cell of area $dKdK^*$ we compute
the corresponding articles density. We colored boxes using a decimal logscale. Blue and
orange circles respectively represent the top 100 articles from $vR$ and $cR$. Top 10 of
both $vR$ and $cR$ are labeled. Circle radius is decreasing with the rank.

**SQL dumps.** In case of the network based on SQL data, we see a difference
when we keep information related to the "Main Page". For English edition
SQL, this article isn’t a dangling node anymore. Wikipedia regularly suggests
to users a set of articles in this main page. By removing "Main Page" related
information, some interesting high PageRanked articles are missing: "Brexit",
"Impeachment inquiry against Donald Trump", "2019 Southeast Asian haze" for
wcpv PageRank and "English Wikipedia" and "QR code" for wcpv CheiRank.
Obviously Main Page is the top 1 for wcpv PageRank and CheiRank.

In case of applying our method to SQL dumps, keeping "Main Page" leads
to new information. Larger tables of top 100 articles are available at [6].

5.2 Multilingual network

A simple way to build a multilingual Wikipedia network is to aggregate networks
corresponding to each considered edition (11 languages). wcpv method weights
the link $A \rightarrow B$ with clicks summed over all considered editions.

Here, we show results and discuss the case of both XML and SQL based mul-
tilingual Wikipedia network considering 11 languages: Chinese, English, French,
German, Italian, Japanese, Spanish, Persian, Polish, Portuguese, Russian.

Regarding table 4 we see that the wcpv PageRank’s top 10 presents more
differences for XML than for SQL version of the network. In context of SQL,
the top 10 wcpv PageRank is very different from both $vR$ and $cR$. Moreover,
sovereign countries only appear for SQL version. As for the case of only English,
$K^*_{wcpv}$ is very far from $K^*_{nowc}$ as we can see with table 5 whether it’s XML.
or SQL. We also have fewer articles related to lists in case of the multilingual Wikipedia network. Unlike the English Wikipedia network, we miss information about social related articles in top 10 \textit{wcpv} with XML dumps. Articles related to actual social trend is found only with SQL (ex: "It: Chapter Two" and "Once Upon a Time in Hollywood").

The top 10 Wikipedia articles \textit{wcpv} using 2DRank for XML multilingual network is much closer to \textit{vR} compared to other rankings. SQL dumps leads to a top 10 \textit{wcpv} 2DRank far from \textit{vR}. Top 10 \textit{wcpv} 2DRank elements with rank in $[2, 4]$ are very unexpected, their corresponding rank in other lists are at least equal to $5287$ (\textit{cR}) and at last $605770$ (\textit{vR}). These articles are of social interests "Queen of the South", Alice Braga", "La Reina del Sur". Note that Alice Braga is a main character of this TV series. In case of SQL \textit{wcpv} top 10 2DRank, we found 4 sovereign countries "United States", "Japan", "Italy" and "Russia" which are not present in \textit{nowc} 2DRank top 10.

| Name                                           | \textit{K}_{wcpv} | \textit{K}_{wc} | \textit{K}_{nowc} | \textit{K}_{cR} | \textit{K}_{vR} |
|------------------------------------------------|-------------------|-----------------|------------------|----------------|----------------|
| Whitehouse (BBR) railway station                | 1                 | 26520           | 14084            | 29208          | 1              |
| List of Ollywood films of 1995                  | 2                 | 9681845         | 9731304          | 5296204        | 2              |
| Union City, Montana                             | 3                 | 1               | 1                | 18             | 10             |
| Quad Electroacoustics                           | 4                 | 161596          | 303835           | 31985          | 647946         |
| Under the Mountain                              | 5                 | 12              | 12               | 84             | 4427566        |
| Allabed-e Olya                                  | 6                 | 123244          | 2093566          | 6223           | 9592595        |
| New Iceland                                     | 7                 | 24              | 21               | 149            | 241328         |
| German coastal battery Tirpitz                  | 8                 | 14              | 15               | 747            | 64             |
| Dear Peggy                                      | 9                 | 1229829         | 9763129          | 417            | 3              |
| Framestore                                      | 10                | 6               | 2                | 2081           | 2890807        |
| List of Queen of the South episodes             | 1                 | 152700          | 9402560          | 1              | 1              |
| International Standard Book Number              | 2                 | 2               | 1                | 12422          | 6820           |
| United States of America                        | 3                 | 4               | 5                | 3              | 596            |
| Queen of the South                              | 4                 | 128752          | 782421           | 33017          | 32562          |
| Geographic coordinate system                    | 5                 | 1               | 4                | 27224          | 4161           |
| Wikidata                                        | 6                 | 3               | 2                | 1666566        | 578987         |
| Virtual International Authority File            | 7                 | 5               | 6                | 2151988        | 77438          |
| English                                         | 8                 | 6               | 3                | 371            | 2227           |
| Library of Congress Control Number              | 9                 | 8               | 7                | 1713259        | 91064          |
| Japan                                           | 10                | 26              | 19               | 175            | 1992           |

\textbf{Table 4.} First 10 articles obtained by PageRank with \textit{wcpv} model from the Multilingual Wikipedia network obtained with XML and SQL dump. Source: own calculations in October 2019

Regarding fig. 3 as for the English version of Wikipedia network, we see that CheiRanks’ overlapping with other CheiRanks and with both \textit{cR} and \textit{vR} are lower than for PageRanks. In case of multilingual version, the exact overlap $\eta_O$ is higher but still low compared to $\eta_N$ values. Regarding both SQL and XML dumps, \textit{wc} is the most similar to \textit{nowc} with respectively $\eta_N = 0.8$ and 0.81. While PageRanks are more similar and CheiRanks related overlaps are almost 0 for SQL, XML version leads to more different tops 100 for PageRank. \textit{cR} and \textit{vR} have the same similarities with $K_{wc}$ (resp. $K^*_{wc}$) and $K_{wcpv}$ (resp. $K^*_{wcpv}$) for both XML and SQL.
Table 5. First 10 articles obtained by CheiRank with \( \text{wcpv} \) model from the multilingual Wikipedia network obtained with XML and SQL dump. Source: own calculations in October 2019

| Name                                      | \( K_{\text{wcpv}} \) | \( K_{\text{wc}} \) | \( K_{\text{nowc}} \) | \( K_cR \) | \( K_vR \) |
|-------------------------------------------|------------------------|----------------------|------------------------|------------|------------|
| Dear Peggy                                | 4                      | 2                    | 1276                  | 417        | 3          |
| List of windmills in Canada               | 2                      | 1                    | 15                    | 72901      | 0822      |
| Israel O’Quinn                            | 3                      | 5                    | 1162187               | 2          | 8          |
| Whitehouse (BBR) railway station          | 4                      | 489                  | 36630                 | 292081     | 1          |
| Israel Hamukoglu                          | 5                      | 9                    | 205286                | 16         | 24         |
| List of Oilywood films of 1995            | 6                      | 3                    | 40098                 | 740        | 31         |
| List of Argentine operas                  | 7                      | 779206               | 4811147               | 5296204    | 2          |
| David Rubinstein                          | 8                      | 755132               | 1598490               | 1124082    | 1009997    |
| Milton Friedman                           | 9                      | 7                    | 313956                | 150        | 5523887    |
| Johnny King                               | 10                     | 10                   | 397574                | 32         | 2097244    |

Fig. 3. Overlap \( \eta_N \) versus rank \( j \) for doublet of ranking lists computed from \( \text{wc} \), \( \text{wcpv} \) and \( \text{nowc} \) models (left panels), from \( \text{wc} \), \( \text{wcpv} \), \( \text{cR} \) and \( \text{vR} \) (right panels). Inset plots correspond to exact overlap \( \eta_0 \). Top row is for multilingual Wikipedia network built with XML dumps and bottom row is for network built with SQL dumps.
We present in fig. 4 the articles’ distribution in \((K, K^*)\) plane for \(wcpv\) in case of both XML and SQL multilingual Wikipedia network. The articles are still organized along the diagonal line and the top 100 from \(cR\) and \(vR\) are gathered in the bottom left corner of the plots. Unlike SQL dumps, in case of XML dumps, the green circles corresponding to top 100 \(vR\) have better PageRank than articles from top 100 \(cR\). The top 100 \(vR\) articles are more scattered in case of XML than SQL dumps.

In case of a multilingual Wikipedia network, \(wcpv\) method brings articles of social interest to the top of PageRank and CheiRank. Moreover, by changing the dump from SQL to XML, articles from both top \(vR\) and top \(cR\) have better PageRanks.

\[\text{Fig. 4. Density distribution of Wikipedia articles in case of } wcpv \text{ XML dumps (left) and SQL dumps (right). The same color code as in fig. 3.}\]

6 Conclusion and future works

Wikipedia gives us plenty of free information related to a large spectrum of knowledge. Articles in this free encyclopedia are edited, checked and corrected by various users (even anonymous). A standard use of PageRank and other related ranking algorithms give a time robust ranking of articles whereas clickstream and pageviews based ranking reflects statistical social trends. In this study, we present an altered version of PageRank, CheiRank and 2DRank by using both clickstream and pageviews data together with connections between Wikipedia articles. "WikiClick Plus View" (\(wcpv\)) model of the Wikipedia network gives different rankings of Wikipedia articles. With \(wcpv\) we measured the centrality of articles in Wikipedia network regarding the actual social interest. We showed that the two type of Wikipedia dumps (XML and SQL) may give different results in final rankings. \(wcpv\) model gives the top PageRank articles related to
actual social interest and the top CheiRank articles that are not related to lists (as they usually are) but rather related to entry point of interest. Instead of roughly aggregating individual language edition based Wikipedia networks to build a multilingual network, the use of \textit{wcpv} method permits us to define a more realistic linkage between articles, by using clickstream data as weight and pageviews as teleportation matrix. Merging both the ephemeral aspect of social trends with time robustness of links based on historical truth, we think that this method can be used for further interesting results.

In future works, we plan to provide a deeper analysis on advantages that can give proposed novel versions of PageRank, CheiRank and 2DRank using social impact in different fields. In this work, we only used data from October of 2019. In our next works, we plan to investigate differences between results of the measures from various time periods of the content of the Wikipedia articles, pageviews and clickstream data. Based on such time dependent data, we would be able to find out the correlation between social impact and evolution of the articles on selected language versions and also on multilingual level. Such data can also be useful to analyse how the indirect social flow between articles lead to the creation of new links. Another interesting direction of the research would be to find out how the proposed measures influences quality of the content in Wikipedia. Using these measures as additional predicting variables could also improve existing prediction models of stock market moves and performances (including price of cryptocurrencies), success of the products or demand for services, as well as electoral predictions and forecasting epidemics in the specified territory.

Wikipedia is one of the representatives of wiki services. Therefore methods proposed in the paper can be also valuable for any knowledge base created using MediaWiki open source software, including corporate ones. These knowledge bases can contain information about customers, products and other business oriented content. Therefore our method can provide new information to companies allowing them to understand social trend’s evolution and help to improve products recommendations for customers, as well as improve existing prediction models related to stock market moves, demand for services, elections results and others.

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References

1. Alexa: Wikipedia.org traffic, demographics and competitors. \url{https://www.alexa.com/siteinfo/wikipedia.org}
2. Brin, S., Page, L.: The anatomy of a large-scale hypertextual Web search engine. Computer Networks and ISDN Systems 30(1), 107–117 (Apr 1998).
3. Coquidé, C., Lages, J., Shepelyansky, D.L.: Contagion in bitcoin networks. In: Abramowicz, W., Corchuelo, R. (eds.) Business Information Systems Workshops. pp. 208–219. Springer International Publishing, Cham (2019)
4. Coquidé, C., Lages, J., Shepelyansky, D.L.: World influence and interactions of universities from Wikipedia networks. Eur. Phys. J. B 92(1), 3 (Jan 2019).
5. Coquidé, C., Lages, J., Shepelyansky, D.L.: Crisis contagion in the world trade network (2020). [https://arxiv.org/abs/2002.07100](https://arxiv.org/abs/2002.07100)
6. Coquidé, C. and Lewoniewski, W.: Supplementary materials. [http://data.lewoniewski.info/pagerank2020/](http://data.lewoniewski.info/pagerank2020/)
7. ElBahrawy, A., Alessandretti, L., Baronchelli, A.: Wikipedia and digital currencies: Interplay between collective attention and market performance. arXiv preprint arXiv:1902.04517 (2019)
8. English Wikipedia: Help: Link. [https://en.wikipedia.org/wiki/Help:Link](https://en.wikipedia.org/wiki/Help:Link)
9. English Wikipedia: Help: Namespace. [https://en.wikipedia.org/wiki/Wikipedia:Namespace](https://en.wikipedia.org/wiki/Wikipedia:Namespace)
10. English Wikipedia: Help: Wikitext. [https://en.wikipedia.org/wiki/Help:Wikitext](https://en.wikipedia.org/wiki/Help:Wikitext)
11. English Wikipedia: Wikipedia: Pageview statistics. [https://en.wikipedia.org/wiki/Wikipedia:Pageview_statistics](https://en.wikipedia.org/wiki/Wikipedia:Pageview_statistics)
12. English Wikipedia: Wikipedia: Red link. [https://en.wikipedia.org/wiki/Wikipedia:Red_link](https://en.wikipedia.org/wiki/Wikipedia:Red_link)
13. English Wikipedia: Wikipedia: Redirect. [https://en.wikipedia.org/wiki/Help:Redirect](https://en.wikipedia.org/wiki/Help:Redirect)
14. Eom, Y.H., Aragón, P., Laniado, D., Kaltenbrunner, A., Vigna, S., Shepelyansky, D.L.: Interactions of Cultures and Top People of Wikipedia from Ranking of 24 Language Editions. PLOS ONE 10(3), e0114825 (Mar 2015). [https://doi.org/10.1371/journal.pone.0114825](https://doi.org/10.1371/journal.pone.0114825)
15. Eom, Y.H., Frahm, K.M., Benczúr, A., Shepelyansky, D.L.: Time evolution of Wikipedia network ranking. Eur. Phys. J. B 86(12), 492 (Dec 2013). [https://doi.org/10.1140/epjb/e2013-40332-5](https://doi.org/10.1140/epjb/e2013-40332-5)
16. Ermann, L., Chepelianskii, A.D., Shepelyansky, D.L.: Toward two-dimensional search engines. J. Phys. A: Math. Theor. 45(27), 275101 (Jun 2012). [https://doi.org/10.1088/1751-8113/45/27/275101](https://doi.org/10.1088/1751-8113/45/27/275101)
17. Ermann, L., Frahm, K.M., Shepelyansky, D.L.: Spectral properties of Google matrix of Wikipedia and other networks. Eur. Phys. J. B 86(5), 193 (Apr 2013). [https://doi.org/10.1140/epjb/e2013-31090-8](https://doi.org/10.1140/epjb/e2013-31090-8)
18. Espin-Noboa, L., Lemmerich, F., Walk, S., Strohmaier, M., Musen, M.: HopRank: How Semantic Structure Influences Teleportation in PageRank (A Case Study on BioPortal). In: The World Wide Web Conference. pp. 2708–2714. WWW '19, ACM, New York, NY, USA (2019). [https://doi.org/10.1145/3308558.3313487](https://doi.org/10.1145/3308558.3313487)
19. Gildersleve, P., Yasseri, T.: Inspiration, captivation, and misdirection: Emergent properties in networks of online navigation. In: Cornelius, S., Coronges, K., Gonçalves, B., Sinatra, R., Vespignani, A. (eds.) Complex Networks IX. pp. 271–282. Springer Proceedings in Complexity, Springer International Publishing (2018). [https://doi.org/10.1007/978-3-319-73198-8_23](https://doi.org/10.1007/978-3-319-73198-8_23)
20. Hickmann, K.S., Fairchild, G., Priedhorsky, R., Generous, N., Hyman, J.M., Deshpande, A., Del Valle, S.Y.: Forecasting the 2013–2014 influenza season using wikipedia. PLoS computational biology 11(5), e1004239 (2015)

21. Khadivi, P., Ramakrishnan, N.: Wikipedia in the tourism industry: forecasting demand and modeling usage behavior. In: Twenty-Eighth IAAI Conference (2016)

22. Kristoufek, L.: Bitcoin meets google trends and wikipedia: Quantifying the relationship between phenomena of the internet era. Scientific reports 3, 3415 (2013)

23. Lages, J., Patt, A., Shepelyansky, D.L.: Wikipedia ranking of world universities. Eur. Phys. J. B 89(3), 69 (Mar 2016). https://doi.org/10.1140/epjb/e2016-60922-0

24. Langville, A., Meyer, C.: Google’s PageRank and beyond: the science of search engine ranking. Princeton University Press, Princeton (2006)

25. Latif, M.H., Afzal, H.: Prediction of movies popularity using machine learning techniques. International Journal of Computer Science and Network Security (IJCNSNS) 16(8), 127 (2016)

26. Lewoniewski, W., Węcel, K., Abramowicz, W.: Multilingual ranking of wikipedia articles with quality and popularity assessment in different topics. Computers 8(3), 60 (2019). https://doi.org/10.3390/computers8030060

27. Lewoniewski, W.: Measures for quality assessment of articles and infoboxes in multilingual wikipedia. In: International Conference on Business Information Systems. pp. 619–633. Springer (2019)

28. Mestyán, M., Yasseri, T., Kertész, J.: Early prediction of movie box office success based on wikipedia activity big data. PloS one 8(8), e71226 (2013)

29. Moat, H.S., Curme, C., Avakian, A., Kenett, D.Y., Stanley, H.E., Preis, T.: Quantifying wikipedia usage patterns before stock market moves. Scientific reports 3, 1801 (2013)

30. Page, L., Brin, S., Motwani, R., Winograd, T.: The pagerank citation ranking: Bringing order to the web. Tech. rep., Stanford InfoLab (1999)

31. Rollin, G., Lages, J., Shepelyansky, D.L.: Wikipedia network analysis of cancer interactions and world influence. PLOS ONE 14(9), e0222508 (Sep 2019). https://doi.org/10.1371/journal.pone.0222508

32. Rollin, G., Lages, J., Shepelyansky, D.L.: World Influence of Infectious Diseases From Wikipedia Network Analysis. IEEE Access 7, 26073–26087 (2019). https://doi.org/10.1109/ACCESS.2019.2899339

33. Thompson, N., Hanley, D.: Science is shaped by wikipedia: Evidence from a randomized control trial. Social Science Research Network (2018)

34. Wikimedia Downloads: English wikipedia latest database backup dumps. https://dumps.wikimedia.org/enwiki/latest/

35. Wikimedia Meta-Wiki: Research: Wikipedia clickstream. https://meta.wikimedia.org/wiki/Research:Wikipedia_clickstream

36. Wikipedia Meta-Wiki: List of wikipedias. https://meta.wikimedia.org/wiki/List_of_Wikipedias

37. Yasseri, T., Bright, J.: Wikipedia traffic data and electoral prediction: towards theoretically informed models. EPJ Data Science 5(1), 22 (2016)

38. Yu, A.Z., Ronen, S., Hu, K., Lu, T., Hidalgo, C.A.: Pantheon 1.0, a manually verified dataset of globally famous biographies. Sci Data 3(1), 1–16 (Jan 2016). https://doi.org/10.1038/sdata.2015.75

39. Zhirov, A.O., Zhirov, O.V., Shepelyansky, D.L.: Two-dimensional ranking of Wikipedia articles. Eur. Phys. J. B 77(4), 523–531 (Oct 2010). https://doi.org/10.1140/epjb/e2010-10500-7