OpenAlex2Pajek

an R Package for converting OpenAlex bibliographic data into Pajek networks

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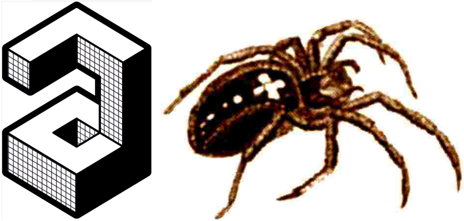

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OpenAlex

“OpenAlex is a fully open catalog of the global research system. It’s named after the ancient Library of Alexandria and made by the nonprofit OurResearch” [18, 13, 17].

OpenAlex launched in January 2022 with a free API and data snapshot. It is considered an alternative to the Microsoft Academic Graph, which retired on Dec 31, 2021 [8]. OpenAlex is based on 7 types of units (entities): **W**ork, **A**uthor, **S**ource, **I**nstitution, **C**oncept, **P**ublisher, or **F**under. It solves some important questions for the analysis of bibliographic data:

1. identification of bibliographic units (IDs, disambiguation)
2. free access (share derived data, download to your machine)
3. improving content through user participation (submit a request)

. . . OpenAlex

OpenAlex opened a space for the development of **higher-level bibliographic services** using bibliographic data analysis to advise the user. For example: a selection of reviewers, a selection of a journal to publish an article, an analysis of publication activity of a research group or institution, etc.

We developed in R a package of functions `OpenAlex2Pajek` [14] for constructing bibliographic networks from selected bibliographic data in OpenAlex. Currently, OpenAlex2Pajek contains three main functions `OpenAlex2PajekCite`, `OpenAlex2PajekAll`, and `coAuthorship`.

In 2007, we developed the Python program `WOS2Pajek` for constructing bibliographic networks from selected bibliographic data from WOS (Web of Science). OpenAlex2Pajek is based on experiences gained using this program.

Creating the collection of bibliographic networks

We split the process of creating the collection of bibliographic networks into two parts:

- determining the set W of relevant works using the saturation approach [5, page 506],
- creation of the network collection for the works from W.

The set W is determined iteratively using the function `OpenAlex2PajekCite` and the collection is finally created using the function `OpenAlex2PajekAll`.

After each run of the function `OpenAlex2PajekCite`, we read the last version of the citation network into Pajek [9] and apply macro `expNodes` to it. It produces a vector of expansion nodes. Using the vector-Info button in Pajek we get a list of works with the largest input degree.

. . . Creating the collection of bibliographic networks

We select an appropriate threshold and extract (select and copy) the upper part of the table into TextPad. In TextPad, we remove other columns and save the list of works as a CSV file. Using the function `joinLists` we combine the old list of works with the new one and save it for the next step of the saturation procedure.

The collection contains the citation network **Cite** and two-mode networks: authorship **WA**, sources **WJ**, keywords **WK**, countries **WC**, and work properties: publication year, type of publication, the language of publication, cited by count, countries distinct count, and referenced works.

Mark Batagelj [2] used this approach to make a collection of networks on the topic of handball. In some cases, such as all works of researchers from a selected institution, the saturation phase is not needed.

Co-authorship between world countries

From OpenAlex we can collect the data about the co-authorship between world countries. To get a selected country, for example, SI, collaboration list we use the query

https://api.openalex.org/works?filter=authorships.countries:SI&group-by=authorships.countries

We developed a function coAuthorship that creates a temporal network describing the co-authorship between world countries in selected time periods. It turned out that OpenAlex is using the current ISO 3166-1 alpha-2 (2024) two-letter country codes to represent countries, dependent territories, and special areas of geographical interest. It doesn't consider ex-countries such as SU (Soviet Union) or YU (Yugoslavia) – such allocations are transformed into the corresponding current countries. Another problem in creating the co-authorship network between world countries is that the above query returns information about up to 200 most collaborative countries. The problem is resolved by considering the symmetry of the co-authorship data.

. . . Co-authorship between world countries

paper	countries
W2001947224	SI, US, SI
W2021064255	ES, SI, ES, ES
W1984191816	AU, SI, AU, AU, AU, SI
W2096814473	SI, DE, IT, IT, IT, IT
W2514227811	ES, ES, ES, SI, ES
W1981385379	US, SI, SI

$$
\mathbf{Co} = \begin{array}{c} \\ \mathrm{AU} \\ \mathrm{DE} \\ \mathrm{ES} \\ \mathrm{IT} \\ \mathrm{SI} \\ \mathrm{US} \end{array}
\begin{array}{c} \begin{array}{cccccc} \mathrm{AU} & \mathrm{DE} & \mathrm{ES} & \mathrm{IT} & \mathrm{SI} & \mathrm{US} \end{array} \\
\left[\begin{array}{cccccc}
1 & & & & 1 & \\
 & 1 & & 1 & 1 & \\
 & & 2 & & 2 & \\
 & 1 & & 1 & 1 & \\
1 & 1 & 2 & 1 & 6 & 2 \\
 & & & & 2 & 2
\end{array}\right] \end{array}
$$

. . . Co-authorship between world countries

The co-authorship between countries can be measured in different ways [3]. What exactly the information obtained from OpenAlex is measuring? To answer this question, we applied the query to 6 papers listed in the first table. In the second table, we have the corresponding co-authorship matrix $\mathbf{Co} = [Co[a, b]]$.

In the co-authorship matrix **Co**, non-existing links are represented with the value NA. We see: let W be the set of works with co-authors from at least 2 different countries. $W_a \subseteq W$ is the set of works with an author from the country a. For $a \neq b$, $Co[a, b] = |W_a \cap W_b|$ – the number of works with co-authors from countries a and b; and $Co[a, a] = |W_a|$ – the number of works co-authored by authors from country a. Let us denote the row sum $R(a) = \text{woutdeg}(a) = \sum_b Co[a, b]$.

Using the function `coAuthorship` we created the sequence of co-authorship networks for each year from 1990 till 2023. They are available at GitHub/bavla [15].

Skeletons

To get insight into the structure of a large network we can reduce it to its skeleton by removing less important links and/or nodes [4].

- Most often the spanning tree, link cut, or node cut are used.
- In the closest k-neighbor skeleton for each node, only k of the largest incident links are preserved. The resulting skeleton is invariant for monotonic transformations of weights.
- The Pathfinder algorithm was proposed in the 1980s by Schvaneveldt et al. [19]. It removes from the network with a dissimilarity weight all links that do not satisfy the triangle inequality – if a shorter path exists that connects the link's end nodes then the link is removed.
- Cores are a very efficient tool to determine the most cohesive (active) subnetworks [6]. The subset of nodes $C \subseteq V$ induces a weighted degree (or Ps) core at level t if for all $v \in C$ it holds $\text{wdeg}_C(v) \geq t$, and C is the maximum such subset. The cores are nested.

Weighted cores

To identify the most collaborative groups of countries we applied the **weighted cores** procedure to the co-authorship networks for the years 1990 and 2023.

The results are presented in the following two tables. The main core in the year 1990 at level 9791 consists of US, GB, and CA. Authors from each of these three countries co-authored with the authors from the other two countries at least 9791 works. Expanding the main core with JP, DE, and FR we get the core at level 9720 – authors from each of the core countries co-authored with the authors from other core countries at least 9720 works. Etc. We notice a huge increase in the number of (joint) publications per year $192486/9791 = 19.66$. In 1990 the top 45 countries contained large or developed countries and (not small) European countries.

The membership and also the ordering of countries in both tables didn't change much. In 2023, CN entered the main core and JP moved to a lower position; some medium-sized East European countries SK, BG, HR, SI, RS, and TH left the list and were replaced by larger developing countries SA, TR, IR, MY, ID, and AE.

Nodes with the highest weighted degree core levels in the year 1990

i	c	t	i	c	t	i	c	t
1	US	9791	16	IN	4124	31	KR	1736
2	GB	9791	17	RU	3950	32	ZA	1656
3	CA	9791	18	PL	3818	33	SK	1532
4	JP	9720	19	DK	3284	34	BG	1338
5	DE	9720	20	AT	2966	35	PT	1326
6	FR	9720	21	CZ	2894	36	AR	1202
7	IT	7394	22	BR	2446	37	EG	1130
8	CH	6884	23	HU	2424	38	HK	888
9	NL	6884	24	NO	2406	39	CL	810
10	AU	6614	25	FI	2406	40	TH	768
11	SE	4880	26	MX	2388	41	SG	756
12	IL	4818	27	TW	2308	42	HR	630
13	CN	4682	28	GR	1878	43	SI	630
14	BE	4682	29	IE	1816	44	PK	630
15	ES	4598	30	NZ	1756	45	RS	588

Nodes with the highest weighted degree core levels in the year 2023

i	c	t	i	c	t	i	c	t
1	AU	192486	16	BR	124582	31	HK	84360
2	US	192486	17	DK	113534	32	EG	82306
3	GB	192486	18	KR	109702	33	ZA	79442
4	IT	192486	19	AT	107734	34	GR	78064
5	CN	192486	20	NO	105640	35	IE	77326
6	DE	192486	21	PT	101980	36	IR	77278
7	CA	192486	22	PL	97686	37	TW	75296
8	FR	192486	23	SA	95528	38	MY	71816
9	ES	182268	24	PK	88758	39	MX	69732
10	NL	178488	25	CZ	84430	40	AR	66660
11	CH	171110	26	TR	84430	41	CL	63632
12	JP	151956	27	IL	84430	42	AE	57136
13	IN	151956	28	RU	84430	43	ID	57136
14	BE	136554	29	FI	84430	44	NZ	56120
15	SE	134726	30	SG	84360	45	HU	50820

1-neighbor skeleton

A simple spanning skeleton that contains all network nodes is the **1-neighbor skeleton** – for each node only its strongest link is preserved.

The resulting directed network is forest-like. In an analysis of weighted networks, the 1-neighbor skeleton is often used to get an overall picture of the network's basic structure.

Nontrivial connected components in the 1-neighbors skeletons are (usually) directed trees with a pair of nodes linked in both directions with the largest weight in the tree – these two arcs are usually replaced by an edge (undirected link).

1-neighbor skeletons

for years 1990, 1995, 2000, 2010, 2015, and 202

We see that the number of isolated nodes (countries not collaborating with other countries) is decreasing.

In all analyzed years the US has a leading (hub) position.

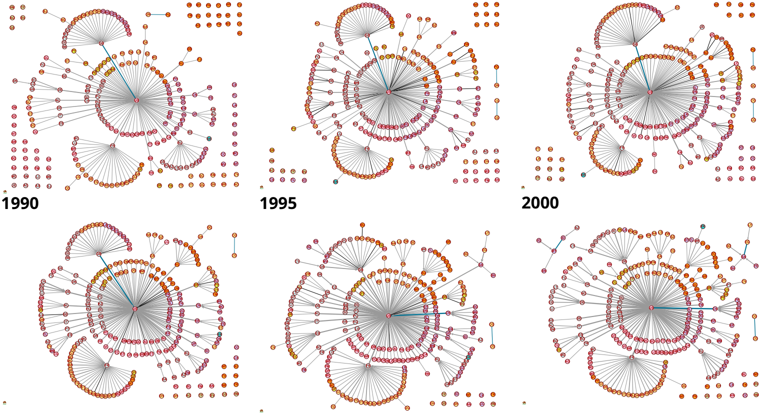
In the years 1990, 1995, 2000, and 2010 the edge in the main component links US and GB but in the years 2015 and 2020 GB is replaced by CN.

In 1990, stronger secondary hubs were GB, FR, RU, JP, and DE. In the following years, some other countries SE, ES, AU, CN, BR, ZA, and IN (BRICS) became secondary hubs attracting previously non-collaborating countries or geographically or linguistically close countries.

In the year 2020, we have two interesting small components: some Arabic countries SD, LY, BH, and YE linked to SA and EG, and some Muslim countries BN, IQ, and AZ linked to MY and ID.

1-neighbor skeletons

for years 1990, 1995, 2000, 2010, 2015, and 2020



1990

1995

2000

2010

2015

2020

Matrix representation

The standard graph-based visualization of a dense network with more than 10 nodes is unreadable. A much better option for networks of moderate size (some hundreds of nodes) is the **matrix representation**.

Another problem is the large range of the weights (for example 1:69440 in 2023) and their distribution. This problem is usually solved using some order-preserving (monotonically increasing) transformation of weights such as $w' = \sqrt{w}$ or $w' = \log w$. In the following, we used the transformation $w' = \log_2 w$ which reduces the range in our example to 0:16.0835 .

An important parameter of the matrix representation is the ordering of the nodes (matrix rows and columns). Some orderings produce blocks in the matrix representation revealing the internal structure of the network. For subsets of nodes R and C, we denote by (R, C) the block (submatrix) determined by rows R and columns C.

Matrix representation

Clustering

To find an interesting ordering is a task of blockmodeling [10]. An approach is to use the **hierarchical clustering** of the co-authorship network/matrix Co. To do this we have to define a dissimilarity $D[a, b]$ between nodes a and b in a co-authorship network. When computing the dissimilarity $D[a, b]$ it is important to use a corrected dissimilarity. We selected the **corrected Euclidean distance** [10, p. 181]

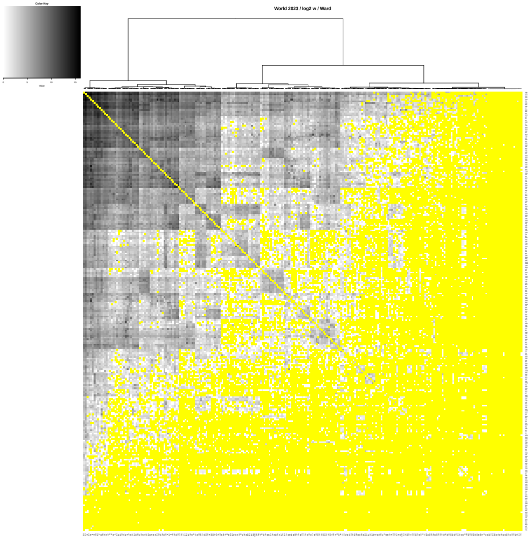
$$D[a, b] = \sqrt{(C[a, b] - C[b, a])^2 + (C[a, a] - C[b, b])^2 + \sum_{c:c \neq a, c \neq b} (C[a, c] - C[b, c])^2}$$

where **C** is a valued network matrix.

For clustering co-authorship networks, we transformed the weights using $w' = \log_2 w$ – a balance between the structure (links) and weights. It is also convenient for visualization.

Matrix representation

World 2023 clustering



A yellow cell represents no-link (absence of co-authorship), and a gray cell represents the intensity of co-authorship – the darker the cell, the stronger the collaboration.

Matrix representation

World 2023 clustering

```
 C1 = { GB, US, AU, CA, CN, IN, FR, ES, DE, IT, BR, BE, NL, CH, AT },
 C2 = { FI, IE, GR, IL, UA, HU, RO, CZ, PL, RU, TR, JP, KR, PT, DK,
        NO, SE },
 C3 = { EC, PE, AR, CL, CO, MX, BD, TH, PH, VN, HK, NZ, SG, TW, NG,
        ZA, ID, MY, IR, AE, PK, EG, SA },
 C4 = { LV, EE, LT, CY, RS, BG, SK, HR, SI },
 C5 = { ET, GH, KE, CM, TZ, UG },
 C6 = { MA, DZ, TN, KW, OM, IQ, QA, JO, LB },
 C7 = { GN, GM, SL, BI, MG, GA, NE, TG, CG, CD, BJ, CI, ML, BF, SN,
        BW, NA, MZ, RW, MW, ZM, ZW },
 C8 = { HT, NI, DO, SV, HN, CR, UY, VE, PR, BO, PA, CU, GT, PY },
 C9 = { NP, LK, KH, MN, MO, BN, MM, AF, SS, BH, PS, LY, SY, SD, YE },
C10 = { KG, TJ, MD, XK, ME, AZ, BY, AM, GE, KZ, UZ, MK, AL, BA, LU,
        IS, MT },
C11 = { JM, TT, FJ, PG, MU, SO, LA, BT, MV, BB, GD, AG, CW, KN, RE,
        GF, NC, PF, GP, MQ, GL, AD, FO, BS, SC, LI, MC, MR, CF, TD,
        LS, SZ, GY, LR, AO, GW, CV, ST, DM, BZ, LC, GI, FK, BM, SJ,
        SR, KY, VI, TL, WS, GU, PW },
C12 = { KP, TM, ER, AW, SX, DJ, YT, GQ, JE, GG, IM, SM, MF, AQ, VA,
        CK, TO, VU, NR, KI, SB, MP, AS, FM, MS, VG, KM, MH, UM, TC,
        AI, VC},
C13 = { EH, WF, TV, GS, PM, SH, BL, PN, NF, NU, AN, HM, TF, CC, BV,
        AX, BQ, IO, CX, TK }.
```

Clustering

From the matrix representation, we first observe the core-periphery structure of the co-authorship network with the core C1-C6, semi-periphery C7-C10, and periphery C11-C13. The core countries cooperate with each other and with many other countries. The semi-periphery countries are collaborating with most of the core countries and only some of the periphery countries. The clusters in the semi-periphery are collaborating internally but there is little collaboration between different clusters. The periphery countries are collaborating mostly with the core countries and with some semi-periphery countries. There is almost no collaboration between the periphery countries – with some exceptions such as {BB, GD, AG, CW, KN} (Lesser Antilles) and {RE, GF, NC, PF, GP, MQ} (French islands). Cluster C13 consists of (almost) inactive countries.

Very dark cells, such as (CN, HK), (CN, MO), (HK, MO), (RU, TJ), and (UA, MZ), indicate strong collaboration between these countries. The same holds for darker rectangles in the picture, such as ({ZA, NG}, C5) (inside Africa), ({MY, IR, AE, PK, EG, SA}, C6) (leading Muslim countries with a group of Arabic countries), ({BH, PS, LY, SY, SD, YE}, C6) (two groups of Arabic countries), (FR, {RE, GF, NC, PF, GP, MQ}) (France and French islands), etc.

Inspecting the row/column of a selected country we get insight into its collaboration with other countries.

Matrix representation

Normalizations

The intensity of co-authorship strongly depends on the (population) size of both countries. To make countries comparable some normalizations are used, such as [12]

1. **Stochastic** $M[a,b] = \dfrac{Co[a,b]}{R(a)}$
2. **Jaccard** $J[a,b] = \dfrac{Co[a,b]}{Co[a,a] + Co[b,b] - Co[a,b]}$
3. **Salton** (cosine) $S[a,b] = \dfrac{Co[a,b]}{\sqrt{Co[a,a].Co[b,b]}}$

In our analysis, we will use another normalization – **activity** or **Balassa** normalization.

Matrix representation

Balassa normalization

Let $Q(a) = windeg(a) = \sum_b Co[b,a]$ denote the column sum for the country a, and $T = \sum_{a,b} Co[a,b]$ the total sum of weights in the network. In our network $R(a) = Q(a)$. Then $R(a)/T$ is the probability of activity of country a. The expected weight $E[a,b]$ from a to b is equal to:

$$E[a,b] = R(a) \cdot Q(b)/T$$

The measured weight $C[a,b]$ may deviate by a factor $A(a,b)$ from the expected value, $C[a,b] = A(a,b) \cdot E[a,b]$, or [21, p. 633]

$$A(a,b) = C[a,b] \cdot T/(R(a) \cdot Q(b))$$

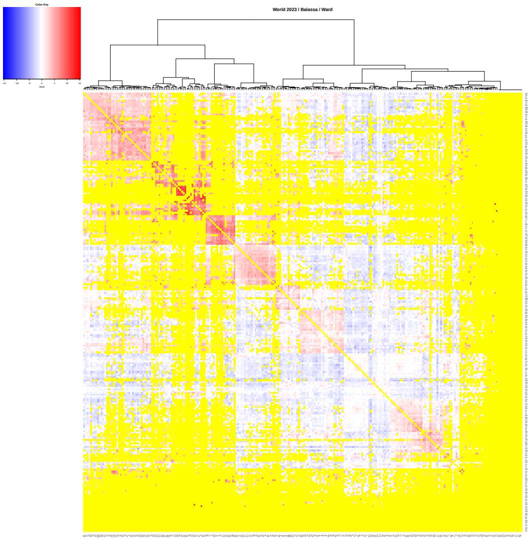
If $A(a,b) > 1$ the measured weight is larger than expected. The deviation measure A is called the activity index (also the Balassa index or the "revealed comparative advantage" [1]). The range of A is not 'symmetric'. To symmetrize it, we apply a logarithmic function to it [20]). For easier interpretation, we selected base 2 logarithms:

$$B(a,b) = \log_2 A(a,b), \text{ for } A(a,b) > 0$$

If $B(a,b) = 0$, the collaboration equals the expected value. In our analysis, we used the index B. We have $A(a,b) = 0$ for non-linked countries. We set $B(a,b) = 0$ in such cases.

Matrix representation

World Balassa 2023 clustering



A yellow cell represents no-link (absence of co-authorship), a red cell – activity higher than expected, and a blue cell – activity lower than expected; the darker the cell, the stronger the collaboration.

Matrix representation

Clustering

```
 B1 = { GH, NG, ET, ZA, RW, TZ, KE, UG, MW, BW, ZM, ZW, NA, LR, LS,
        SZ },
 B2 = { GN, GW, AO, MZ, CF, TD, GQ, GA, BI, ML, CI, SN, CG, CD, BJ,
        BF, CM, NE, MR, TG, SO, GM, SL },
 B3 = { JE, MS, GP, MF, RE, GF, MQ, MV, SC, MG, MU, PF, YT, CK, PW,
        MP, AS, FM, GU, MH, NU, TK, SB, TO, WS, PG, FJ, NC, KI, NR,
        VU },
 B4 = { BS, JM, TT, VI, KY, BM, TC, LC, AI, VC, GY, CW, AG, GD, KN,
        BB, DM },
 B5 = { BR, AR, CL, CO, MX, EC, UY, GT, PY, CU, PE, VE, PA, BO, CR,
        SV, HN, NI, DO, PR, HT, BZ, SR },
 B6 = { BT, TL, BN, ID, BD, TH, VN, MM, MN, NP, PH, LK, KH, LA },
 B7 = { OM, BH, PS, KW, LB, QA, AE, MY, SA, IQ, EG, JO, IN, PK, IR,
        TR, MA, DZ, TN, SS, SD, AF, YE, LY, SY },
 B8 = { PT, ES, NL, BE, CH, IE, DK, FI, NO, SE, IL, AT, DE, IT },
 B9 = { HK, MO, TW, CN, KR, GB, CA, US, NZ, SG, AU, JP },
B10 = { GR, PL, CZ, HU, MT, EE, LV, LT, SI, RO, BG, HR, SK, RS, BA,
        MK, XK, AL, ME },
B11 = { UZ, KG, AZ, KZ, TM, BY, AM, GE, TJ, RU, MD, UA },
B12 = { GL, AD, FO, LI, MC, FR, CY, IS, LU },
B13 = { KM, CV, ST, KP, DJ, ER, AW, SX, GI, FK, SJ, AQ, VA, SM, IM,
        GG, SH, AX, IO, VG, PN, TV },
B14 = { EH, WF, UM, GS, PM, BL, NF, AN, HM, TF, CC, CX, BQ, BV }.
```

Matrix representation

Balassa normalization

The diagonal blocks are mostly red or at least white – the inside cluster activity is larger than expected. The activity between most of the African countries from B1 and B2 is intensified. A very strong activity is between Pacific islands PW, MP, AS, FM, GU, MH and also inside the cluster of Caribbean islands B4. The almost white diagonal blocks on the West European countries B8 and other developed countries B9 tell us that their collaboration is as expected. So is the collaboration between the West European countries B8 and the East European countries B10.

Most of the out diagonal blocks are blue – less active than expected. An exemption is a block (B1-B4, MA, DZ, TN, SS, SD, AF, YE, LY, SY). There are some isolated dark red cells such as (WS, PU), (KI, TV), and (LC, AW) and some small red blocks such as (GN, GW, AO, MZ, CV, ST) and (AW, SK, BB, AG, CW). There are also some blue "lines" – mostly noncollaborative countries such as MO, HK, TJ, and SA.

Conclusions

The article presents the first version of the R package OpenAlex2Pajek. There are some improvements planned.

First, we will try to do the entire conversion in R. We will also expand the range of acquired data units and program a version of the package that performs the conversion from a local copy of the database.

OpenAlex is a rich source of bibliographic data relatively easy to use also from user's programs so enabling more demanding analyzes of bibliographic data. Here, it is important to ensure high data quality [7], and OpenAlex users can play a big role with their feedback.

Acknowledgments

The computational work reported in this paper was performed using a collection of R functions `OpenAlex2Pajek` and the program Pajek for the analysis of large networks. The code, data, and color figures in PDF are available at Github/Bavla/OpenAlex [14].

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