Changes in the connection networks of MEPs

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Introduction

By its plastic nature, human connections change over time, especially when outside effects take place. However, in the case of policy makers, such changes will sooner or later have consequences to our life (As we live in the EU.)

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- **Identifying key decision and policy makers.**
- **How events and occurrences shape the form and topology of the network.**

All of these are helpful in understanding the processes regarding proposals and how they evolve into enacted laws.

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- A more recent topic of interest might be the Russian-Ukrainian conflict and how it altered connections within the European Parliament.
- For now, we focused on gathering information on **the whole dataset at once**, and we will focus on the changes over time in future research

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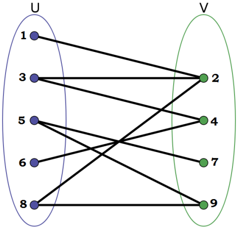
A bipartite graph:



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We have also considered and implemented weighted projection. We used the so called: "Collaboration weighted projection" (where we reward secluded document matching and punish popular document matching)

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Country	Contributions
Germany	5539
France	4242
Spain	3853
Italy	3550
Poland	2531
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Lithuania	541
Cyprus	502
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Country	Contributions per million people
Malta	1181.76
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More seats are given to smaller countries to boost their influence in the EP

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Country	Contributions per MEP
Luxembourg	103.83
Malta	102.33
Slovenia	95.00
Slovakia	92.38
Cyprus	83.67
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Poland	49.63
Lithuania	49.18
Italy	48.63
Czechia	48.57
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So the **MEPs of smaller countries contribute more** on average

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EP Group	Ideology	MEPs (pre-Brexit)
European People's Party (EPP)	center-right, conservative	176 (182)
Socialists and Democrats (S&D)	social democrat, progressive	144 (154)
Renew Europe (RE)	liberal, pro-Europe	101 (108)
Greens-European Free Alliance (Greens/EFA)	green, regionalist, pro-Europe	73 (72)
European Conservatives and Reformists (ECR)	conservative	66 (62)
Identity and Democracy (ID)	nationalist, euroskeptic	62 (73)
European United Left/Nordic Green Left (GUE-NGL)	socialist, euroskeptic	37 (41)
Non-inscrits (NI)	various	46 (57)

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"Non-inscrits" is a French term for "non-aligned"

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ECR	62	34.16
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There is also a tendency for larger EP groups to contribute more.

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Hilde Vautmans	RE	183
Karen Melchior	RE	173
Marc Angel	S&D	169
Olivier Chastel	RE	167
Łukasz Kohut	S&D	166
Michal Šimečka	RE	160
Michal Wiezik	EPP	152
Ramona Strugariu	RE	151
Petras Auštrevičius	RE	151
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They mostly come from the more left-wing EP Groups such as RE or S&D.

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Karen Melchior	RE	0.1058
Michal Šimečka	EPP	0.1031
Olivier Chastel	RE	0.0998
Marc Angel	S&D	0.0947
Ramona Strugariu	RE	0.0943
Sophia in 't Veld	RE	0.0892
Łukasz Kohut	S&D	0.0884
Nicolae Ştefănuță	RE	0.0867
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As we can see, we have very similar results to the degree centrality

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Maria Grapini	S&D	0.0128
Petras Auštrevičius	RE	0.0128
Charlie Weimers	ECR	0.0123
Annalisa Tardino	ID	0.0117
Maria da Graça Carvalho	EPP	0.0116
Sophia in 't Veld	RE	0.0109
Maria Noichl	S&D	0.0109
Luisa Regimenti	ID	0.0107
Sirpa Pietikäinen	EPP	0.0100

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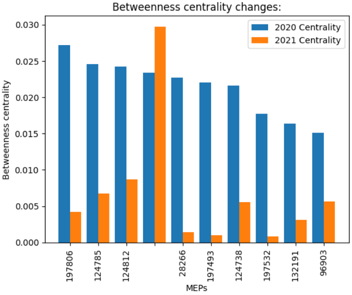
These MEPs are different compared the eigenvector centrality list which was *mostly* the repetition of the Degree centrality list.

Behavior of central nodes

Betwenness centrality

2020 as basis:



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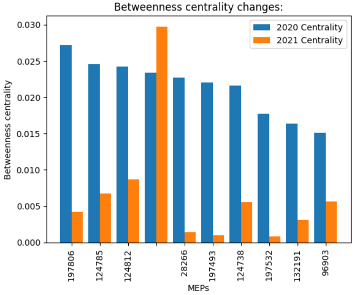
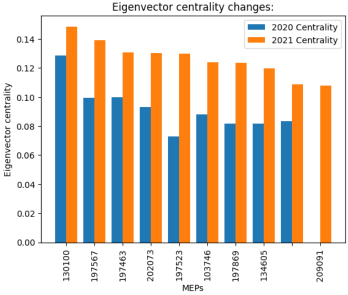


Eigenvector centrality
2021 as basis:



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Some visualizations of the MEP social network graph (there were also some 0 degree nodes):

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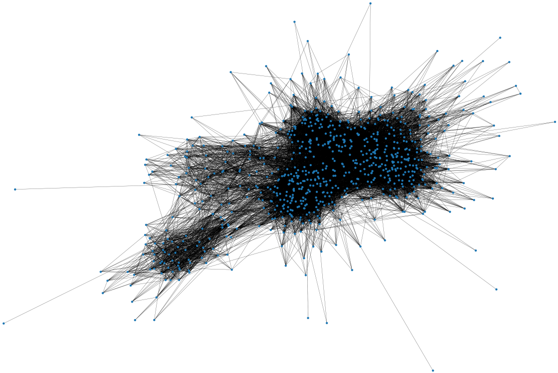

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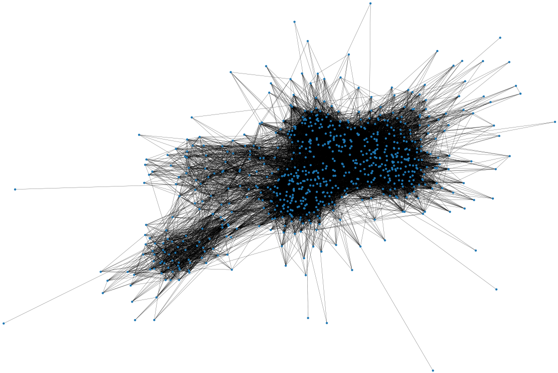

The Smaller interval ones look similar, however they aren't necessarily connected like this one

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Color coding the nodes (according to EP groups):

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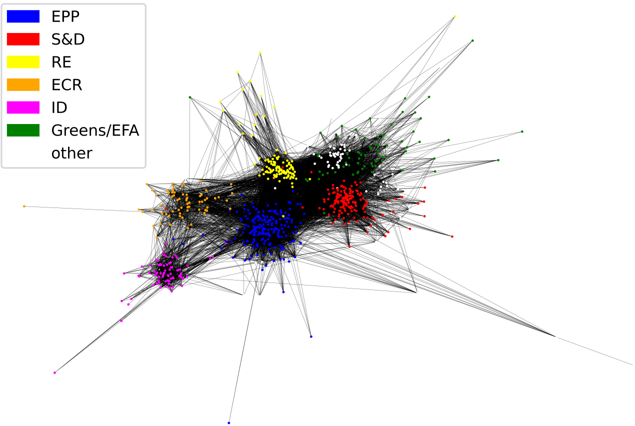

What's next?

We require additional data for multiple reasons:

- Cutting at more relevant dates, for finer distiction.

  Further consideration might be fruitful, namely, the further useage of weighted projection. (Some machine learning opportunity)

Thank you for your attention!