PNAS RESEARCH ARTICLE | APPLIED MATHEMATICS
SOCIAL SCIENCES

# Social Network and Text Analysis of Debates in the house of commons of the 58th parliament of the United Kingdom

Meike Hanneke Roëlle Bos[a,1], Max Bürkner[b,1,2], and Gerard Ramos Pomar[a,1]

This manuscript was compiled on December 10, 2025

**This study examines the interaction network of the 58th UK House of Commons by extracting MP-to-MP exchanges from parliamentary debate transcripts using a large language model classifier. The resulting directed and weighted network reveals a dense structure characterised by heavy-tailed interaction intensities and hierarchical tendencies. Analysis of the network backbone shows that members of the governing Conservative Party overwhelmingly dominate the core of parliamentary discourse, reflecting their governing role during this period. Community detection identifies approximately twelve moderately cohesive groups whose structure is not driven by party but by areas of expertise. Word-frequency analysis demonstrates that these communities cluster around substantive topics such as defence, housing regulation or foreign-affairs, indicating that MPs align their interactions with policy specialisation rather than partisan boundaries. Sentiment analysis shows an overall moderate and narrow distribution of emotional tone across MPs, yet also reveals systematic influence effects: the most positive and most negative MPs significantly shift the sentiment expressed by those who interact with them. Finally, longitudinal analysis indicates a gradual decline in average sentiment across the full electoral period, suggesting a worsening emotional climate in parliamentary discourse during years marked by political and global turbulence. Together, these findings highlight how structural influence, expertise, and emotional tone shape the dynamics of democratic deliberation.**

parliamentary debates | network analysis | community detection | sentiment analysis

With one of the world's longest-standing democratic institutions, the UK Parliament functions as a central arena where political priorities are articulated, negotiated, and ultimately transformed into policy. Decisions made in the House of Commons shape both domestic and international agendas. Yet beyond the formal procedures and party structures, politics is fundamentally enacted through human interaction: networks of MPs form, dissolve, and reconfigure as members position themselves within debates, respond to one another, and express their views in ways that can directly influence policymaking. Parliamentary discourse is therefore not merely a record of spoken statements, but a reflection of the relational dynamics through which political power and influence flow.

Recent years have been marked by historically significant events, including the COVID-19 pandemic, the Taliban takeover of Afghanistan, or the Russian invasion of Ukraine, that have reshaped political priorities and heightened societal tension. While it is evident that such events have affected public sentiment across European states, a systematic and empirical understanding of how these shocks manifest within parliamentary discourse remains limited.

Owing to its geopolitical importance, the UK Parliament is uniquely transparent: every spoken contribution is publicly documented, providing one of the most extensive records of political deliberation worldwide. This makes the 58th House of Commons an exceptional case for analyzing political interaction at scale.

## Significance

This study uncovers hidden structural, topical, and emotional patterns within one of the world's oldest democratic institutions. Using computational analysis, supported by a large language model to extract interactions, we show how influence, expertise, and sentiment shape parliamentary discourse. Our findings show that governing-party MPs dominate core interactions, communities form around policy expertise rather than party lines, and sentiment both shifts over time and is influenced by particularly positive or negative speakers. In combining centuries-old parliamentary tradition with state-of-the-art computational analysis, this work illustrates how new technologies can deepen our understanding of democratic behaviour.

Author affiliations: [a]Department of Applied Mathematics and Computer Science, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark

M.B. and G.R.P. sourced the data; M.B. visualized the network; M.H.R.B. analyzed the communities; G.R.P. performed the sentiment analysis; M.H.R.B., M.B., and G.R.P. wrote the paper.

The authors declare no competing interest.

[1]M.H.R.B., M.B., and G.R.P. contributed equally to this work.

[2]To whom correspondence should be addressed. E-mail: s252890@dtu.dk

Across more than four years of turbulence, tens of thousands of exchanges form a dense interaction-based network in which structural roles, topical interests, and emotional expression become visible.

Using a large language model to extract MP-to-MP interactions, we construct a directed and weighted network of parliamentary discourse. This not only allows to study structural patterns, hierarchal tendencies and community detection, but also investigate whether emotional the spreads through the exchanges and how overall sentiment evolves throughout the 58th parliament. In *results* we describe these findings in detail.

## Results

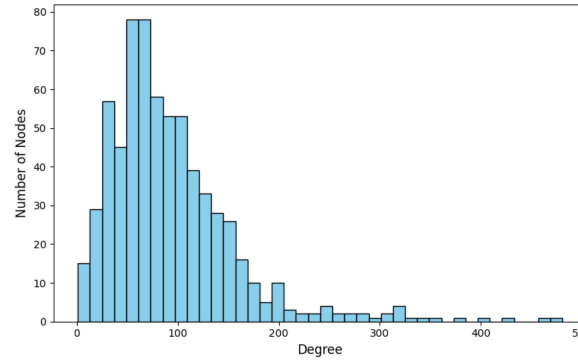
**Network Analysis.** The interaction network of the 58th UK Parliament contains 665 unique MPs, with 30,863 distinct MP-to-MP connections and 86,039 recorded interactions. The graph has a density of 0.13, meaning MPs interacted on average with 93 colleagues. While the degree distribution approximates a Poisson distribution (Figure 1a), the edge-weight distribution is heavy-tailed (Figure 1b), indicating that a small number of MP pairs exchange information far more frequently than the rest.

This suggests that although most MPs maintain a moderate number of connections, a small subset engages in disproportionately intense interaction. These highly active MPs often hold central parliamentary roles and act as focal points in debates. The combination of a near-Poisson degree distribution with a power-law weight distribution shows that differences in interaction intensity, rather than connectivity alone, drive much of the network's structural variation.

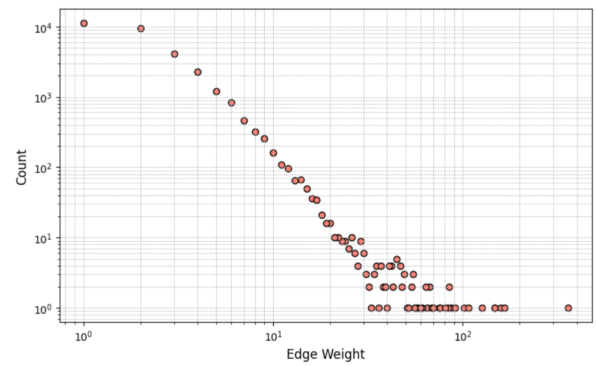
The network displays a negative degree assortativity of −0.18 (1), meaning highly connected MPs tend to interact more with low-degree MPs than with other hubs. Such disassortative patterns typically arise in hierarchical systems, where central figures link to a broad periphery. In Parliament, ministers, shadow ministers, and committee chairs often interact widely with backbenchers, creating a core–periphery structure consistent with the observed heavy-tailed edge weights.

When analyzing centrality measures to identify key parliamentary figures, several MPs emerge as particularly influential within the network. Boris Johnson, for instance, ranks highest across multiple centrality metrics, including in-degree, out-degree, degree, and betweenness centrality (2) caused by his prominent role as Prime Minister during much of the 58th Parliament. Other key figures include his successor Rishi Sunak, Matt Hancock Secretary of State for Health and Social Care during the COVID-19 pandemic and Sir Lindsay Hoyle, the Speaker of the House of Commons. One outlier is Jim Shannon from the Democratic Unionist Party, who also ranks highly across all centrality measures, though not holding a major governmental position. This may be caused by his extraordinary engagement in lesser popular debates (3).

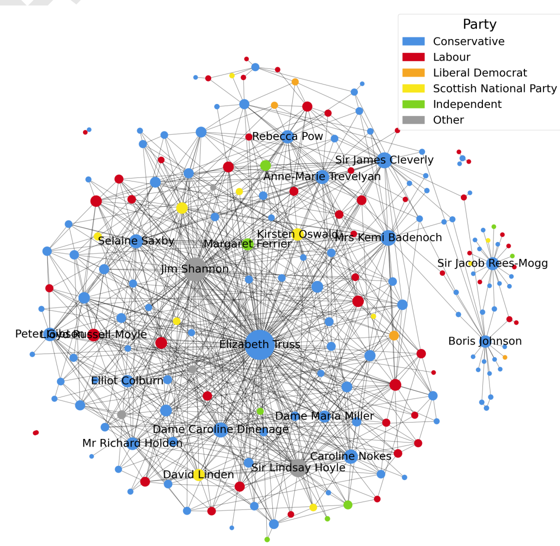
Finally when analysing the backbone of the network using the high salience skeleton method (4) together with edge betweenness centrality, we find that the backbone, as seen in Figure 1c, says within a hairball like structure. This indicates that there are no clear pathways of interactions dominating the parliamentary debates, but rather a complex web of exchanges where many MPs play crucial roles in connecting different parts of the network. Nontheless one more key figure is revealed, Elizabeth "Liz" Truss, who served as Secretary of State for




**(a)** Node degree distribution




**(b)** Edge weight degree distribution




**(c)** Network backbone visualization

**Fig. 1.** Network analysis of the 58th UK Parliament. (a) Node degree distribution showing a near-Poisson pattern, indicating that most MPs interact with a moderate number of colleagues. (b) Edge weight distribution highlighting a heavy-tailed, power-law behavior, reflecting a small subset of MP pairs with disproportionately frequent interactions. (c) Network backbone visualization using high-salience edges, revealing a dense, interconnected structure dominated by Conservative Party MPs, with key figures in prominent parliamentary roles acting as central connectors across the network. Other parties are present but less central.

International Trade and President of the Board of Trade before briefly becoming Prime Minister. Her prominence in the backbone analysis suggests that she was a pivotal connector within parliamentary discussions, likely due to her involvement in high-profile trade negotiations and international relations during a turbulent period for UK politics. Additionally, it becomes apparent that the Conservative party members dominate the backbone structure, reflecting their central role in government and policymaking during this parliamentary term.

**Community Detection.** In parliamentary debate, MPs are not expected to confine their interactions to their own party; politics relies on debate, negotiation, and cross-party exchange. The interaction network of the House of Commons clearly reflects this, as modularity scores based on the six parties are negative across all sessions and the full electoral period. This indicates that MPs consistently engage broadly across party lines, regardless of political context or composition.

Community detection nevertheless proves highly informative. As shown in Table 1, the Louvain algorithm identifies roughly twelve communities in each network, typically containing between 60 and 130 MPs who interact more frequently with one another. Two very small communities were excluded from further analysis due to limited interpretability.

| | Full | Session 1 | Session 2 | Session 3 | Session 4 |
|---|---|---|---|---|---|
| Communities | 12 | 12 | 12 | 13 | 11 |
| Modularity | 0.182 | 0.267 | 0.289 | 0.278 | 0.343 |

**Table 1. Louvain community structure and modularity scores across full dataset and parliamentary sessions**

The modularity scores of the detected communities range from 0.182 to 0.343. These values are moderate and indicate that connections within communities are only slightly denser than would be expected in a random network. Given the nature of the UK House of Commons as a highly interactive and debate-driven environment, this pattern is expected. MPs from different communities frequently engage with one another; the communities simply identify groups that interact somewhat more often than others.

Within these detected communities, the distribution of party membership also reveals meaningful patterns. The Conservative MPs have a stable share in all Louvain detected communities, which matches their global share. This pattern is not surprising: the Conservatives won the 2019 general election and formed the government (5), meaning they held the largest number of seats and were structurally embedded across a wide range of debates. Government parties typically participate broadly and consistently in parliamentary discussions, which naturally result in a stable representation across interaction-based communities. Other parties, however, reveal that there may be more underlying the community structure. Smaller parties show stronger deviations in their community share, sometimes being strongly overrepresented and sometimes strongly underrepresented. This suggests that certain communities may be shaped around specific topics or areas of expertise. Smaller parties often specialise in particular policy domains, and when debates align with these domains, their MPs become disproportionately active. MPs with relevant expertise are more likely to speak on these topics and to engage with other MPs who share similar expertise. The distribution of party shares within communities therefore indicates that interactions may be driven by topic-focused or expertise-driven clustering.

To inspect expertise or dominant topics within the parties and communities, wordclouds are created based on an overuse score. This score is computed by comparing how frequently a word appears in a party or community to how often the same word appears in the rest of the dataset. The idea is that words which are relatively more common within one group signal specialised topics or expertise. For each word, two relative frequencies are calculated: the probability of the word occurring in the target group ($p_c$), and the probability of the word occurring in all other groups combined ($p_r$). The overuse score is the ratio of these two probabilities.

$$p_c = \frac{\text{count of word in target}}{\text{total words in target}}, \qquad p_r = \frac{\text{count of word in rest}}{\text{total words in rest}}, \qquad [1]$$

A high score means that the word is used much more frequently within the target group than outside it, highlighting distinctive terminology. These word clouds showed distinct differences in the topics discussed, shown in table 2.

| Community | Inferred Topic |
|---|---|
| 11 | Education & Covid |
| 10 | Defence & Geopolitics |
| 9 | Local Transport Issues |
| 8 | Housing Regulation |
| 7 | Israel Gaza Conflict |
| 6 | Environment & Fisheries |
| 3 | Law & Regulation |
| 2 | Northern Ireland Politics |
| 1 | Wales & Justice |
| 0 | Immigration & Borders |

**Table 2. Inferred dominant topics per community based on wordclouds.**

These results can, in some cases, be directly linked back to the party representation within each community. For instance, the Liberal Democrats are strongly present in Community 8, whose wordcloud indicates a dominant focus on housing regulation. Community 7, where debates appear heavily centered on foreign affairs and specifically the Israel–Gaza conflict, shows a clear overrepresentation of the Scottish National Party. This aligns with the fact that the SNP frequently engages in humanitarian and foreign-policy discussions (6). Furthermore, the parties grouped under "Other" align strongly with Community 2, which focuses on Northern Ireland politics. This pattern points to the presence and influence of the Northern Irish party within this cluster. Overall, this topic–community analysis clearly highlights that communities form around areas of expertise: MPs moderately cluster around the substantive issues they specialise in and actively debate.

**Sentiment Analysis.** Understanding how emotional expression is conveyed in the Parliament is key to capturing the broader dynamics of political debate. Therefore, sentiment analysis is applied to the interactions in the 58th UK Parliament to explore this dimension.

Firstly, the analysis focuses on whether emotional tone spreads through interactions. If positive or negative rhetoric influences the behaviour of others, MPs who consistently speak with highly positive or highly negative sentiment are expected to affect the tone of those who engage with them.

To test this, the average sentiment of each MP across all their contributions is calculated, resulting in the distribution shown in Figure 2.

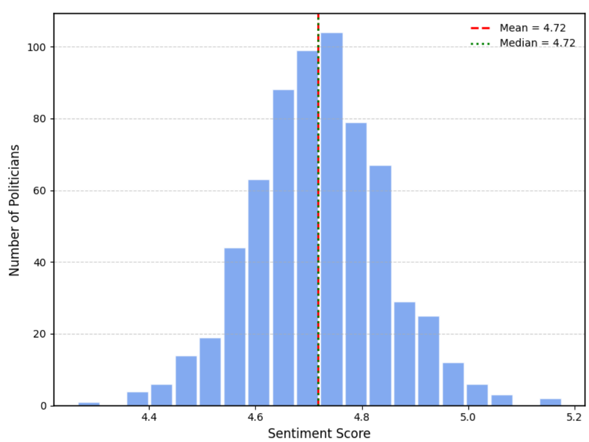



**Fig. 2.** Distribution of MPs average sentiment during the 58th Parliament.The mean sentiment across MPs is 4.72, with a variance of 0.02, indicating relatively neutral sentiment with low dispersion. Scores range from approximately 4.2 to 5.2, with a few extreme outliers.

Samples of thirty MPs with the highest, lowest, and mean-adjacent sentiment are obtained to represent speakers with positive, negative, and neutral tones. The sentiment of all MPs when interacting with these three groups is examined to assess measurable effects. To ensure reliability, MPs must have at least ten direct interactions; otherwise, they are excluded, since the sentiment analysis tool has limitations with small text samples such as individual contributions. As noted in prior research (7), sentiment analysis can be unreliable for shorter texts due to ambiguity. The mean and standard deviation of MPs' sentiment when interacting with the three groups are summarized in Table 3.

| Group | Mean | Std Dev | N |
|---|---|---|---|
| Neutral | 4.718 | 0.069 | 30 |
| Happy | 4.828 | 0.070 | 29 |
| Sad | 4.674 | 0.095 | 27 |

**Table 3. Sentiment statistics for interactions with different politician groups**

To assess whether the average sentiment expressed by MPs differs depending on their interlocutor, two hypothesis tests are conducted: one to determine if MPs express significantly higher sentiment when interacting with the happiest politicians compared to neutral politicians, and another to test if MPs express significantly lower sentiment when interacting with the saddest politicians compared to neutral politicians.

For the first test, the hypotheses are structured as follows:

$$H_0 : \mu_{\text{vs. happy MPs}} = \mu_{\text{vs. neutral MPs}}$$
$$H_1 : \mu_{\text{vs. happy MPs}} > \mu_{\text{vs. neutral MPs}}$$

The test results indicate a t-value of 6.062 with 56.85 degrees of freedom, yielding a p-value of 0. Given that the p-value is less than the significance level of 0.05, we reject the null hypothesis $H_0$ and accept the alternative hypothesis $H_1$. This indicates that MPs express significantly more positive sentiment when interacting with the happiest politicians compared to when interacting with neutral politicians.

For the second test, the hypotheses are:

$$H_0 : \mu_{\text{vs. sad MPs}} = \mu_{\text{vs. neutral MPs}}$$
$$H_1 : \mu_{\text{vs. sad MPs}} < \mu_{\text{vs. neutral MPs}}$$

The test results yield a t-value of -1.976 with 47.14 degrees of freedom, resulting in a p-value of 0.02703. Since the p-value is less than the significance level of 0.05, we reject the null hypothesis $H_0$ and accept the alternative hypothesis $H_1$. This indicates that MPs express significantly more negative sentiment when interacting with the saddest politicians compared to when interacting with neutral politicians.

These findings suggest that emotional tone of a contribution can influence the sentiment expressed by others in subsequent interactions, as shown by the significant differences in sentiment when MPs interact with the happiest versus the saddest politicians. However, it is important to note that this analysis does not measure whether sentiment is contagious. To assess true emotional contagion, one would need to track how sentiment evolves over the course of a debate or series of interactions, rather than just examining immediate responses.

In addition, changes in the emotional climate of Parliament are examined over time to determine whether major disruptions, such as the COVID-19 pandemic or the Russian invasion of Ukraine, leave measurable traces in parliamentary discourse. By tracking sentiment across the 58th Parliament, potential shifts linked to these exceptional events could potentially be identified.

Therefore the average sentiment of all contributions is calculated every two months from December 2019 to May 2024. The resulting time series is displayed in Figure 3 on the next page.

Overall, there is a slight downward trend in average sentiment over the parliamentary term, indicating a gradual increase in negative tone. However, this trend is accompanied by significant fluctuations, suggesting that sentiment varies considerably from month to month. Contrary to expectations, there are no pronounced drops in sentiment that correspond directly with major disruptions; if anything, sentiment appears to rise during these periods. The period with the most positive sentiment occurs between December 2019 and March 2020, coinciding with the initial outbreak of COVID-19. Another notable event,

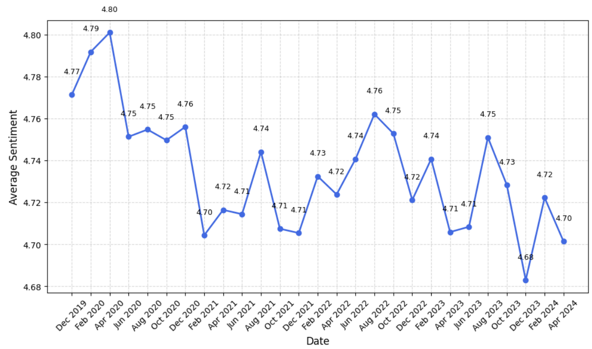



**Fig. 3.** Average Politician Sentiment Over Time During the 58th UK Parliament. Sentiment is calculated every two months, label indicates the first of the two months.Average sentiment shows a gradual decline over the term, punctuated by temporary increases during key political and global events.

the Taliban takeover of Afghanistan in August 2021, corresponds to a local peak in the time series, scoring at least 0.03 points higher than surrounding months. Similarly, the Russian invasion of Ukraine in February 2022 aligns with a local upward trend that culminates in a peak in August 2022.

Although it appears that major disruptions lead to more positive sentiment in parliamentary debates, a more thorough analysis is necessary to draw firm conclusions. For instance, a longer time series would allow for an examination of how sentiment evolved before and after the COVID-19 pandemic. Additionally, generating word clouds for the analyzed months could help assess the prominence of specific events during these periods, and thus their potential influence on overall sentiment. A more granular sentiment analysis, considering shorter time windows or individual debates, could also reveal subtle shifts linked to specific events, providing a more precise picture; however, this might require using a different sentiment analysis tool.

## Discussion

This study has several limitations. The most significant concerns the use of a large language model: AI is a relatively new technique, and although human verification indicated minimal misclassifications, its outputs cannot guarantee the deterministic reliability expected in engineering or statistical modelling. Computational constraints further limited the volume of debates that could be processed. Finally, because governing parties structurally dominate parliamentary debate, findings may be specific to this electoral period alone.

These findings carry several important consequences. Expertise-based communities indicate that policy knowledge, not party identity, structures interaction, which may enhance the quality of deliberation but also concentrate agenda-setting in specialised clusters. The fact that emotional tone propagates through interactions implies that a small number of highly positive or negative MPs can shift the broader atmosphere of debate, with potential consequences for collaboration and civility. Lastly, the declining sentiment trend may signal increasing institutional strain during turbulent political periods.

Future work could analyse multiple electoral periods, as network structure, governing dynamics, and topical pressures are highly context-dependent. A larger longitudinal dataset is essential for drawing general conclusions about parliamentary interaction patterns, community formation, and sentiment dynamics beyond this specific term.

## Materials and Methods

**Empirical Data and Preprocessing.** All data were obtained from the UK Parliament House of Commons via the publicly available Hansard API (8). We specifically targeted debates from the 58th electoral period, corresponding to the period from December 2019 to May 2024. This resulted in a total of 22,585 documented debates within the given timeframe. Subsequently, debates spanning multiple days, which were separated into sub-debates and were therefore difficult to trace, were removed, resulting in a final dataset of 14,719 debates.

As the focus of our analysis was to identify behavior and changes in interactions within the UK Parliament House of Commons, it was necessary to identify and filter pairs of interacting speakers. To achieve this, we used the most recent GPT-OSS-Safeguard:20B large language model from OpenAI (9, 10), with the temperature set to 0 to ensure reproducibility. This reasoning model is specialized in following policies to classify text. In our case, it was provided with the following three criteria to define an interaction: a contribution was considered interacting if the second speaker, anywhere in their utterance: (1) directly addressed the first speaker, (2) built upon a point made by the first speaker, or (3) asked a question referring to the first speaker's contribution. The model was prompted to provide a binary yes/no response.

Qualitative analysis indicated that this model outperformed other open-source LLMs, as it applied reasoning to determine whether the contributions of two given speakers could be classified as interacting. The GPT-OSS-Safeguard:20B was run on an RTX 4070 Ti SUPER for approximately 100 hours, with an 8k-token context window, to classify interactions in 6.001 randomly sampled debates, which formed the basis of our analysis

**Data, Materials, and Software Availability.** All scripts used for data retrieval, preprocessing, and interaction extraction are publicly available on GitHub (11). For direct access to the final dataset feel free to reach out.


1. MEJ Newman, Assortative mixing in networks. *Phys. Rev. Lett.* **89**, 208701 (2002) arXiv:cond-mat/0205405.
2. LC Freeman, A set of measures of centrality based on betweenness. *Sociometry* **40**, 35–41 (1977).
3. Wikipedia, Jim Shannon (https://en.wikipedia.org/wiki/Jim_Shannon) (2025) Accessed 10 Dec 2025.
4. D Grady, C Thiemann, D Brockmann, Robust classification of salient links in complex networks. *Nat. Commun.* **3**, 864 (2012) Publisher: Nature Publishing Group.
5. Uk parliament (https://commonslibrary.parliament.uk/research-briefings/cbp-8749/) (2025) Accessed 9 Dec 2025.
6. Intenational affairs - snp (https://www.snp.org/our-vision/international-affairs/) (2025) Accessed 9 Dec 2025.
7. PS Dodds, KD Harris, IM Kloumann, CA Bliss, CM Danforth, Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitter. *PLOS ONE* **6**, e26752 (2011) Publisher: Public Library of Science.
8. UK Parliament, Hansard API (https://hansard-api.parliament.uk/swagger/ui/index#/) (2025) Accessed 8 Dec 2025.
9. ollama, gpt-oss-safeguard:20b (https://ollama.com/library/gpt-oss-safeguard) (2025) Accessed 8 Dec 2025.
10. OpenAI, et al., gpt-oss-120b gpt-oss-20b model card (arXiv [Preprint]) (2025) arXiv:2508.10925 [cs]. http://arxiv.org/abs/2508.10925. Accessed 8 Dec 2025.
11. M Hanneke Roëlle Bos, M Bürkner, G Ramos Pomar, Social network and text analysis of debates in the house of commons of the 58th parliament of the united kingdom (https://github.com/Unlxgit/socialgraphproject2025/tree/main) (2025) Accessed 10 Dec 2025.