Hidden in plain sight. A co-constitutive approach to unveil misogyny in digital public discourse.

Keywords: data feminism, online misogyny, online social networks, computational linguistic, qualitative content analysis

Extended Abstract

Over the last twenty years, interest has grown for how digital media augment structural misogyny – i.e., aprioristic and general hatred and prejudice against women. An increasing number of studies highlight how social media platforms do not simply "supersize" structural misogyny. Rather, social media enrich the forms in which the misogynistic mortification of women occurs online fostering the viral circulation of misrepresentations that reinforce intersectional patterns of social exclusion (Sobieraj 2020) but also feeding an impressive variety of means to perpetrate online abuse (Watson 2023). Against this background, attempts are multiplying to identify and classify misogynistic contents online (Fersini et al. 2018, Guest et al. 2021) thus contributing to the growing field of "data feminism" (D'Ignazio and Klein 2020) – a research domain where data are conceived of as imbued with intersectional oppression and, at the same time, provide key resources to overcome it.

Our study aims at contributing to this growing research stream by integrating modeling attempts with a neater attention for the sociotechnical mechanisms that support the circulation of misogynistic contents, which we investigate through a co-constitutive methodological approach where network analysis and computational linguistics techniques inform and, at the same time, are informed by qualitative content analysis. We set our gaze on digital public discourse for how it develops on a daily basis on Twitter and dig into its relational and semantic components with a twofold aim. On the one hand, we seek to single out not only cases of overt gendered hatred but also instances of covert misogyny that feed intersectional oppression and invisibilization particularly by discussing women and their experiences instrumentally and in the context of broader dynamics of political conflict. On the other, we try to disentangle the relational logics that support the spread and ensure the persistence over time of misogynistic contents within digital conversations.

We render Twitter conversations in the form of daily networks of "live" interactions (i.e., mentions, replies, retweets) and we examine them according to the following steps:

Step1 – Identification of *conversational pivots*- i.e., nodes with indegree scores higher than a threshold value equal to average indegree plus one standard deviation. Conversational pivots are located within related *conversational areas* – i.e., communities identified via the Louvain algorithm. In order to look at portions of digital discourse that display minimal levels of collectivity, we retain only tweets authored by users belonging to conversational areas with at least one pivot per day.

Step2 – Each daily corpus of tweet is rendered as a list of stems, which is qualitatively inspected and from which a group of *semantic pivots* are isolated – i.e., stems that are qualitatively identified as particularly meaningful with respect to the case observed as they point to either frequently discussed issues or gender-related terms (e.g., stems referring to body parts, gender-derogatory or abusive language etc.).

Step3 – The relevance of selected stems for each daily conversation is evaluated in conjunction with levels of concentration in usage to disentangle overt and covert instances of misogyny, their magnitude within daily portions of conversation and the rhythm at which they persist.
Step4 – Semantic pivots are associated with the types of interactions (tweets, mentions, retweets and replies) that sustain their circulation, which we associate with different sociotechnical mechanism of misogynistic content circulation.
We applied this sequence of steps to analyze the conversation that developed in the Italian Twittersphere in conjunction with the release of Silvia Aisha Romano, an Italian NGO aid-worker kidnapped in Kenya and returned home on 10 May 2020 converted to Islam and wearing a green jilbab. We collected tweets carrying keywords referred to Romano (*silvia* OR *aisha* OR *silviaromano*) from 9 May 2020 (the day her release was announced) to 20 May 2020 (ten days after she landed back in Italy). Our daily rendering of the overall digital conversation resulted in 12 networks (Step 1, table 1).
The qualitative inspection of stem lists (Step 2) allowed us to identify inductively three thematic areas that were relevant to the case and, for each of them, a set of semantic pivots (fig.1 a-c): Romano's body and clothing choices (Panel A), Romano's persona (Panel B), and a set of various themes discussed over time (Panel C): Romano's kidnapping, release, and the ransom paid for her, her conversion to Islam, the Italian government as her rescuer, the alleged enemies she was opening the door to with her conversion (i.e., Islamic terrorists), the online hate channeled on the woman.
The temporal inspection of longitudinal evolution of semantic pivots (Step 3) reveals that, after an overall initial happiness for the announcement of her release (*liberazione, bella*, Panel C), covert misogynistic discursive practices reduced Romano's experience to a matter of costs sustained for her liberation (*riscatto, costare*) and her conversion to *Islam* - the religion of terrorists (*terror**). When attention has been set on her (Panels A and B), overt attacks with slurs (*puttana, troia, stronza*) occur and persist, although her belittling and public mortification passes more often through insistence on her young age (*ragazza, bambina*), which makes users doubt (*dubbio*) about the spontaneity of her conversion, as well as through her reduction to her her clothing choices (*veste, velo*), which appear to be evidently problematic given the number and the persistence of incorrect and derogatory terms with which her jilbab is called (*tunica, tovaglia, saio*).
Finally, the exploration of sociotechnical mechanisms sustaining the circulation and the persistence of semantic pivots shows (Step 4, fig.2) shows that, while overt gendered attacks travel more often that average via retweets (a mechanism we call broadcasted misogyny), more covert forms of misogyny through which Romano is mortified are actively constructed via mentions and tweets - for example, concerns for the cost of her liberation or comments on her clothing choices travel via direct mention more often than average.

References

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	Overall Network		Community			
	N	E	Tot Number	Chosen	% nodes	% edges
9 May 2020	23757	47829	3154	24	83.4 *(19814)*	90,26 *(43170)*
10 May 2020	27025	53057	3165	27	83 *(23141)*	92,31 *(48766)*
11 May 2020	30691	70288	4727	21	81 *(24761)*	90,47 *(63593)*
12 May 2020	20757	44994	3056	21	80.4 *(16688)*	90 *(40495)*
13 May 2020	15733	29356	2359	21	79,25 *(12469)*	87,49 *(25685)*
14 May 2020	7958	11120	1284	28	75,19 *(5952)*	82,03 *(9077)*
15 May 2020	4167	5857	705	22	63,11 *(2630)*	70,21 *(4112)*
16 May 2020	2761	3732	436	16	67,11 *(1853)*	75,24 *(2808)*
17 May 2020	1944	2239	437	16	56,12 *(1091)*	63,38 *(1419)*
18 May 2020	1980	2541	298	16	63,18 *(1243)*	68,13 *(1721)*
19 May 2020	974	1141	216	13	55,33 *(535)*	64,15 *(732)*
20 May 2020	364	343	121	5	31,04 *(113)*	39,36 *(135)*

Table. 1 **Overview of online interactions about Silvia Aisha Romano**.
We quantified the number of nodes and edges for the overall network per each day, the total number of communities found, the number of communities chosen based on the presence of pivotal users and the corresponding percentage of nodes and edges that cover the interactions for the selected communities.

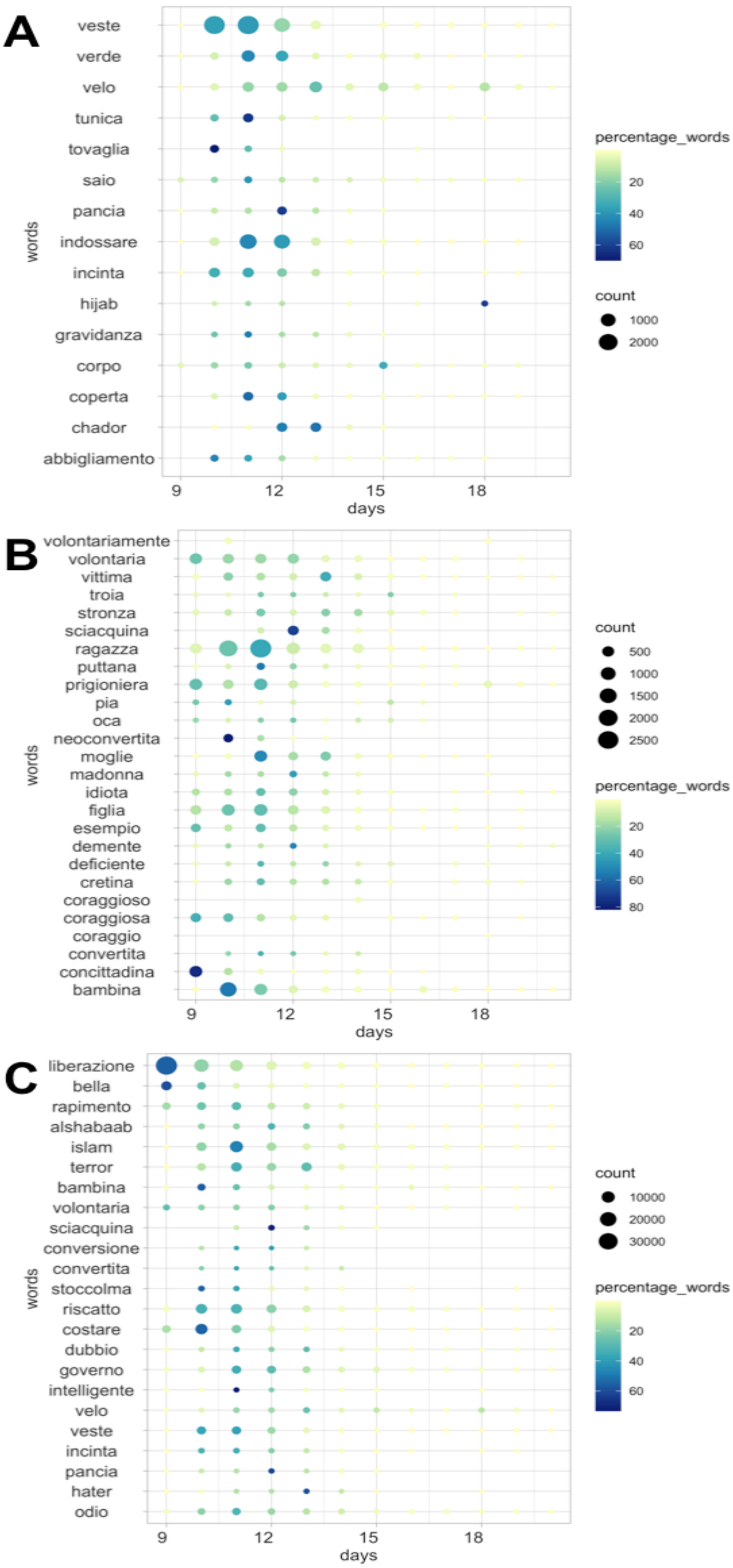

Fig.1 **Distribution of absolute and relative value of semantic pivots**. For each panel (A-C), we quantified the absolute frequency and the relative importance of each word per day. Panel (A) contains semantic pivots referring to Romano's body and clothing. Panel (B) contains semantic pivots that refer to Romano's persona. Panel (C) contains semantic pivots that refer to Romanos' body and persona, her kidnapping, release and the ransom paid, her conversion to Islam, the Italian government as her rescuer, alleged enemies (i.e., Islamic terrorists), the online hate channeled against the woman.

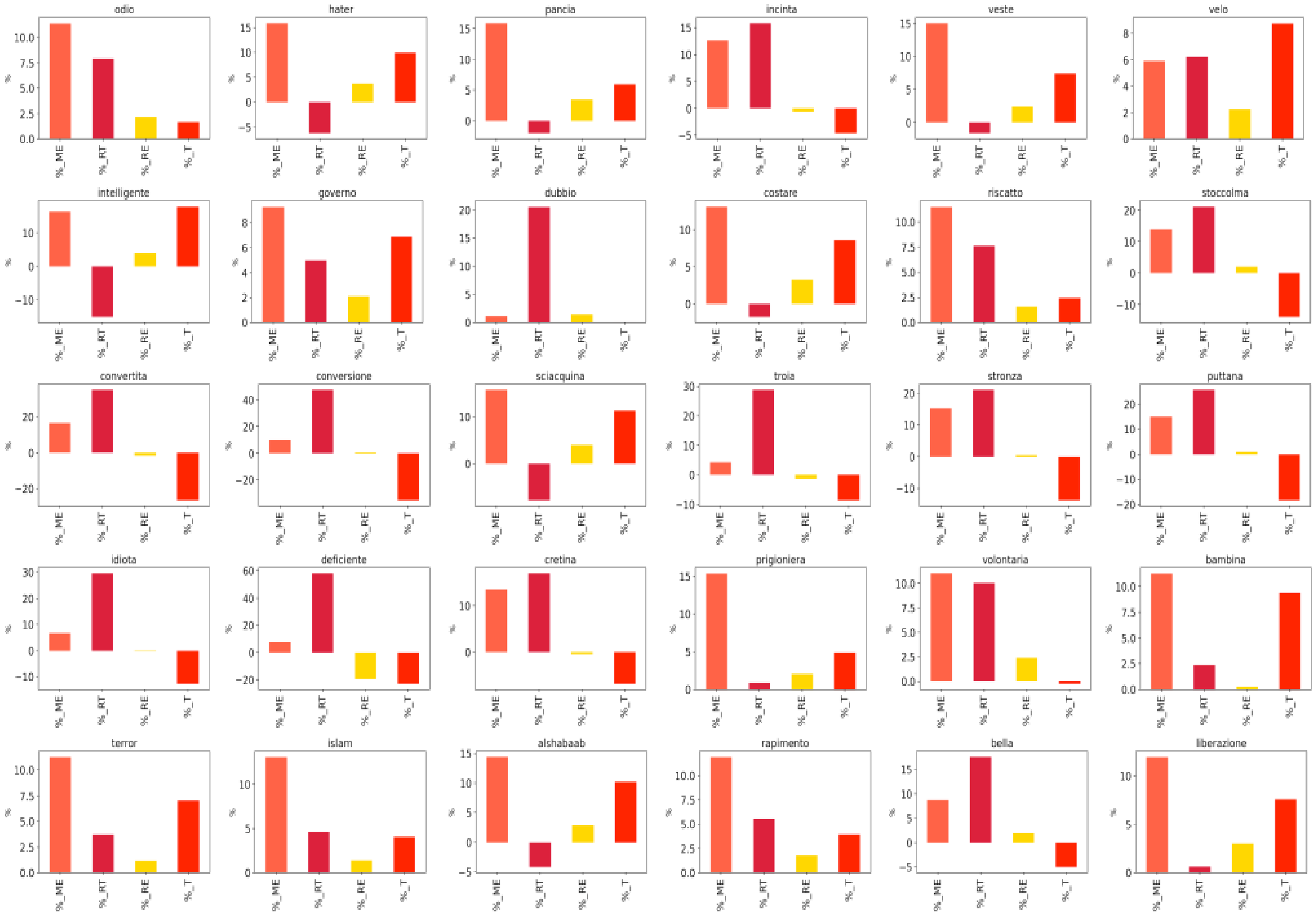

Fig.2 - **Sociotechnical mechanisms supporting the circulation and persistence of semantic pivots**. Bars indicate deviation from average occurrence of mentions, replies, retweets and tweets in the overall dataset