Mapping and Exploring the Dynamics of Inequality Narratives Through Social Media

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In this work, we apply a hybrid-AI framework to analyse online discourse about inequality on Twitter. Our approach integrates knowledge from natural language understanding, knowledge graph-based semantics, and network analysis to identify narratives around inequality and analyse their changes during the COVID pandemic. We present a two-step approach: A bird's-eye perspective on the overall discourse network around inequality maps how the entities, concepts, and events of the narratives are connected by linking these to existing knowledge graphs and can be filtered on tweet metadata such as time. Two connected entities can then be explored in more detail in a fine-grained analysis of how the entities and their relationship are characterised by social media users, highlighting the diffusion of different perspectives on a given topic related to inequality, such as gender, education, and poverty.

CCS Concepts: • **Human-centered computing** → **Interactive systems and tools**; • **Applied computing** → *Sociology*; • **Computing methodologies** → **Semantic networks**; **Discourse, dialogue and pragmatics**.

Additional Key Words and Phrases: social media, social networking sites, network analysis, natural language understanding, knowledge graphs

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1 INTRODUCTION

Humans engage in various types of collaborative activities, some intentional – as the construction of the pyramids, some unintentional – as creating traffic jams – and some that are in between – such as creating a global discourse via social media. In the course of this collaborative effort, so-called *narratives* emerge, spread, and compete with each other. Narratives play a key role in the conceptualization, identification, and comparison of social groups and in the perception of inequalities. They impact how people perceive situations in a wide range by creating, manipulating or diffusing social myths. They can justify or question socio-economic differences and target power structures and hierarchies. Narratives impact how people perceive their surroundings while influencing social antagonisms among social groups. Consequently, they carry social categories containing the diversity in which stories are being told [28]. Social media platforms such as Twitter can nowadays be considered a viable proxy for understanding narratives by citizens, interest group leaders, experts, advocates, and other stakeholders [20].

This work aims to identify and visualize narratives around inequality by integrating natural language analysis of social media posts with formalized knowledge from open-source knowledge graphs (KG). We propose that the *fabula*, – the ground truth about relevant events, entities, and

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concepts in the narrative – is captured in the KG; and that social media users express from their personal point of view the narratives they use to understand these (such as the role that actors play, or causal links between concepts or events). While there have been many works in recent years that aim to extract narratives from text [11, 14], we, instead, consolidate the information from a large corpus of short-form texts into one narrative network, thus linking many different points of view that exist about the same entities.

Our approach builds upon the framework proposed by Spillner *et al.* to analyse conflict narratives [32]. To analyse inequalities, the proposed framework consists of two parts. First, a bird's-eye discourse mapping tool for extracting and mapping entities, including their relations for a specific targeted issue. Second, a fine-grained analysis method that allows us to categorise previously identified entity pairs and their relations to the topic of interest. The latter part includes the different perspectives communicated on social media platforms.

We present an interactive tool that allows users to explore narrative networks both from a bird's-eye view as well as on a fine-grained level, which extends both steps of the original framework. Our method consolidates and validates entities identified in the text through named entity recognition (NER) and linking (NEL). Linking the entities to the DBpedia KG [15] allows us to enrich the narrative network further and, thereby, facilitate its understanding and interpretation through general world knowledge. In addition, the information learned from the natural language texts provides information about how these entities are viewed by people as part of the common discourse on inequality, which is not captured in the KG.

This paper presents how this method can be applied to discussions about inequality on Twitter during the COVID pandemic. Online discussions about inequality are extremely varied and are dependent on the political, economic, social and cultural context. We are interested in how people understand and talk online about multiform inequalities and intersectionality [43], and want to understand which are the perceived causes, driving factors and effects of inequalities, as well as the relations among mentioned entities (people, places, events, organizations, countries, etc.). The chosen time period and the variety of posts on Twitter allow us to explore how inequality narratives developed during a number of political and social changes. Moreover, analysing short and informal social media texts presents a unique challenge in natural language understanding: One tweet usually only presents a small part of an overarching narrative of its author. Understanding these texts requires a large amount of general world knowledge, knowledge about current events, and the ability to abstract from the given information to understand the point of view from which the text was likely written. In connecting the information from a large corpus of texts with that of existing KGs, we show that our approach can reconstruct these overarching narratives.

The contribution of this work is two-fold: The approach we implemented integrates knowledge from natural language understanding with semantic knowledge from KGs, allowing users to explore inequality narratives on social media on two levels - an overview of the narrative network, as well as a detailed view that enriches individual connections to show different points of view. The created tool can be used by the community to get a better understanding of the diverging narrative strands and analyse its components. It further allows anyone to subtract the diverse viewpoints during an ongoing narrative, which we believe can help news media and other sources to observe how the perception and impact of inequality changes over time.

2 METHODS AND PRIOR WORK

2.1 Narrative Understanding

While the term *narrative* is used in the literary sciences to mean the recounting of a series of events in a story, in cognitive science, narratives are understood to be a central means of how we make sense of the world [9]. Because of this, there are very different approaches to narratives in computer science [33]. There is a growing body of work that aims to convert natural language texts (e.g. fairy tails, news stories, or social media posts) into a formal representation of events and related actors [1, 4, 6, 18, 22, 38, 42][1], or to find connections between the textual narrative and an event KG [16]. Meghini *et al.* [16] define the event graph as the *fabula*, which is the basis for the (textual) narrative. In these works, the analysis is generally on the level of a single narrative or a single text per narrative. They presuppose that a narrative is always told from a certain perspective depending on the author or storyteller but do not capture this perspective in formal representation.

In robotics, however, a narrative is a formal representation that describes an event or episode from a certain point of view [23, 24], thus linking events (in terms of physical actions) to the concepts they evoke or actors to the role they play. This kind of narrative thus formalizes a level that is "in-between" the fabula and the textual description of it. A similar narrative model has also been proposed by Kroll *et al.* [13], who differentiate between factual relations in a KG (the fabula) vs hypothetical, narrative relations connecting them. Such formal narratives can be used to generate different natural language descriptions of the same event from different perspectives [24]. Similarly, Mensio *et al.* [18] proposed a framework for natural language understanding in which news articles are compared based on their narrative framing [8] (e.g. based on word choices), so that similar articles can be linked and compared in terms of their narratives.

In the context of understanding social media discourse, we consider the construction of narratives to be a collaborative process between many people. A single tweet does not in and of itself present a complete and independent narrative but rather represents one puzzle piece that can be used to understand a larger network of interconnected, shared narratives. This aligns with the framework proposed in [32], where a *narrative network* is constructed, connecting all the entities which appear in the fabula across the corpus of texts.

2.2 Narrative Network Approach

Our analysis[2] results in two kinds of graphs, which can be visualized and interactively explored to gain insight into the inequality discourse. First, we build a *bird's-eye network* which visualizes the co-occurrences of different entities in the Twitter discourse, showing what role the entities play in the narratives surrounding inequality. Secondly, pairs of these entities that are linked in the bird's-eye network can be analysed in more detail, revealing more of the information learned from natural language analysis in another *fine-grained analysis* graph which "zooms in" on their relationship. Here, we look at how each entity is characterized in the context of the inequality discourse, revealing different points of view that Twitter users have on these entities (descriptors, associated actions, ownership ascriptions, etc.). Additionally, while the bird's-eye graph only shows the relationship between two entities in terms of their co-occurrences in the tweets, the fine-grained graph reveals how the relationship between them is understood (one entity acting on the other, similarities and contrasts, influences, etc).

2.2.1 Dataset. We collected a large corpus of social media posts about inequality that were published on Twitter from the 1st of January 2020 to the 1st of October 2022. For this purpose, using the academictwitteR R package [2], we have downloaded from the Twitter API V2 all posts (excluding retweets) in English published in that time whose text explicitly matches at least one of the following query terms: 'inequality' OR 'inequalities' OR 'inequal'. By choosing generic query terms, we voluntarily apply a very neutral and wide range data capturing strategy, which does not

[1]See also the Text2Story Workshop [11]

[2]The code can be accessed under [we will add the link to our repository here; removed for anonymity].

focus on a particular type of inequality, because we are interested in understanding how the focus and views of inequalities of different types change over the investigated period.

This study focuses on Twitter because it is a generalist social media news platform[26], it was among the most used media in those years, and it provides an API for downloading the data, which is accessible for academic research. However, the implemented approach can be employed with data from other sources and social media platforms. Using Twitter data enforces a common data format and provides access to the metadata provided by the platform, including timestamps and locations, referenced links or media, related posts and reactions (retweets and likes), the popularity of the post, as well as information about its author. Tweets and their authors are already a form of network graph that has previously been analysed through graph analysis [7, 19, 30], and many related studies analyse social media posting activity to understand the dynamics of online arguments and discourse [29, 36, 41].

2.2.2 Natural Language Processing. First, tweet texts are processed using the spaCy NLP toolkit [10]. For the case study presented in Section 3, we processed a random sample of 100.000 tweets from the entire corpus, from which the co-occurrence network is constructed. We employed spaCy for part-of-speech (POS) tagging and dependency parsing together with the DBpedia Spotlight tool [17] to link named entities to DBpedia [15]. Social media-specific tokens such as hashtags are not removed but are instead part of the analysis.

2.2.3 Named Entity Recognition and Linking. NER and NEL machine learning models can be used to identify mentions of named entities such as people, organizations, and locations and link them to KGs. However, instead of building a co-occurrence graph directly from the named entities recognized by the trained model, we instead use its prediction to identify two kinds of entities that are of interest for our analysis. First, the named entities are cross-references with the noun phrases found in the syntactic analysis of the tweets and all those noun phrases of which an entity is a subset of its tokens are collected. Then, the root token of the noun phrase is identified. Consider the following two noun phrases:

(1) *"president Joe Biden"*: Here, the token span "Joe Biden" is identified by the NER as a named entity and linked to the KB entry concerning the person *Joe Biden*. The root of the noun phrase is the token "Biden".
(2) *"the american president"*: Here, "american" is recognized as a named entity and is linked to the KB entry of the *United States of America*. The root of the noun phrase, however, is "president".

In Example (1), the entire noun phrase refers to the entity that was recognized, with the surrounding phrase describing it. The same entity could just as well be described as "Joe Biden" or "Presidential Candidate Biden" or "my neighbour Joe". In cases like this, all noun phrases referring to the same entity are consolidated into one node in the co-occurrence network, which we call a KB entity. The different descriptions characterize these entities. In contrast, in Example (2), the entity identified by the NEL model is not, in fact, the entity that the entire phrase refers to. Depending on the context, it likely refers either to the office of the president of the United States of America or to the person holding the office at a certain point in time (e.g. Joe Biden). In some cases, the entity that the phrase refers to is part of the KG but is not identified correctly through NEL; in other cases, the phrase describes an entity or concept which is not (yet) part of the KG. One example of this is the concept of "vaccine inequality", which appeared during the COVID pandemic. Thus, noun phrases following Example (2) are collected separately as "noun phrase entities" (NP entity) and are not consolidated.

2.3 Birds-Eye Network

2.3.1 Co-occurence Network. The bird's-eye network is constructed of a co-occurrence network of both the NP entities and the consolidated KG entities. Co-occurrences are counted on the level of tweets. From the sample of 100.000 tweets, we collect 201494 occurrences of 73901 unique entities, which means that on average, each tweet contains about two entities. Thus, the resulting graph contains 73901 nodes connected by 157773 edges, with a mean nodal degree of 4.270 (SD = 43.116).

2.3.2 Filtering. Visualization of large and highly-connected graphs is a difficult problem [37], and not all co-occurrences in this network represent meaningful information. Thus, the network has to be filtered to remove less relevant connections. First, spurious connections, that is, edges of weight 1, are removed, splitting the graph into multiple connected components and many unconnected nodes. All but the largest connected component are removed, as these contain parts of the discourse which are only tangentially related to the main inequality narrative.

For large and complex weighted networks, such as the one at hand, it is often difficult to identify the right trade-off between the level of filtration and the amount of relevant information to be preserved in the simplified network representation. In many real-world applications, the probability distribution $P(\omega)$ that any given edge e_{ij} is carrying a weight $w(e_{ij}) = \omega$ is not constant across nodes [31]. When this is the case, a global cutoff based on edge weight does not consider the intrinsic diversity of edges connecting nodes with different structural roles (e.g, hub entities *Vs* bridging entities *Vs* peripheral entities). In the co-occurrence network, edge weights are dependent on the topology of an entity's neighbourhood. In particular, when the number and distributional properties of the weights of incident edges are not uniformly or identically distributed across nodes, a change in the focus toward a local filtration method is useful.

For this reason we have developed an ad-hoc filtration strategy that prunes edges based on their relative relevance for their incident nodes, maintaining relations that are important for both entities connected by the edge. Call E the set of edges of the entities network G and V the set of nodes (i.e., entities) of the entities network G, the proposed filtration algorithm works as follows:

(1) For all edges $e_{ij} \in E$:
   (a) If the weight of the edge $w(e_{ij})$ is above the global threshold, add the edge e_{ij} to the set K of edges *to be kept*;
   (b) If not; then for the two incident nodes i and j of e_{ij}:
      (i) compute the percentile of the weight of the selected edge $w(e_{ij})$ with respect to those of all edges incident to that node;
      (ii) if the percentile is above the local threshold for both incident nodes of the selected edge, add the edge e_{ij} to the set K
(2) remove all edges e_{ij} s.t. $e_{ij} \in E \wedge e_{ij} \notin K$.

2.3.3 Network Clustering. The filtered view of the network contains 683 nodes and 1392 edges (nodal degree: mean = 4.076, SD = 14.349). This subgraph is clustered using the Louvain algorithm, which identifies clusters based on the graph connectivity. The algorithm does not necessarily identify topic clusters, as the clustering is not based on natural language analysis. The filtered subgraph includes 22 connected components, including one large, central component as well as 21 small components of 3-5 nodes. The Louvain algorithm results in 38 clusters: the 21 small connected components and the main component, which is divided into 17 clusters.

2.4 Fine-grained view

In the second network view, one can "zoom in" on pairs of entities connected in the bird's-eye graph. This view extends the more general and (intended to be) impartial knowledge included

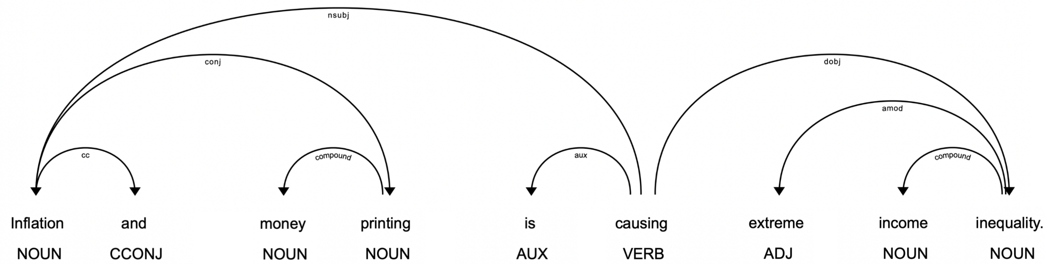


Fig. 1. Example of the dependency structure of a tweet. The text of this tweet was shortened to visualize the example; the full text was: "She is switching cause and effect. Supply chain issues are not causing inflation. Inflation and money printing are and have been disrupting the allocation of means and is therefore causing supply chain issues among other things like extreme income inequality". The graphic was generated using spaCy's dependency visualisation tool.

in KGs with the aggregated perspectives from social media posts. Both the semantic information that can be gained from the tweets in the form of semantic embeddings, as well as the syntactic structure of the tweet, is taken into account. Using this information, the subgraph of a given entity pair is extended with additional nodes containing different characterizations of each entity, and the edge between them is "split apart" into a number of paths that show different ways in which people understand the relationship between the two entities.

2.4.1 Characterization of entities. The first goal of the fine-grained narrative is to understand how two entities are characterized in the context of inequality and of each other. This includes, for instance, the role that is assigned to them, qualities associated with them, terms used to refer to them, or how they are understood to compare to others or change over time. These characterizations are extracted from the tweet text based on its dependency structure. Figure 1 shows the syntactic structure of an example tweet as a dependency graph. The children of the root of each entity noun phrase and their respective subtrees in the dependency tree are aggregated across all occurrences of this entity. In the example shown in Figure 1, the entity "Inflation" has two such characterizing subtrees, "and" and "money printing". For consolidated KB entities which are referred to in different terms, those distinct descriptions here become unique characterizations. The characterizations collected for each entity are sorted by their number of occurrences, weighted with a score s that is calculated as the ratio of tokens that belong to a more descriptive part of speech, e.g. adjectives, as opposed to those belonging to a less descriptive one, e.g. determiners.:

$$s = \frac{|\{t \in T | \text{pos}(t) \in \{\text{noun, verb, adjective, adverb}\}\}|}{|T|} \quad (1)$$

with T the set of tokens in the phrase and $\text{pos}(t)$ the part of speech of a token.

Only characterisations with s greater than the mean are shown in the visualisation. The exception to this rule is if (for comparatively uncommon entities) less than 10 unique characterizations have been found, in which case all of them are shown, or if less than 20 have been found, in which case the top 50% are shown.

Next, we utilize GloVe embeddings [21] [3] to compare characterizations on a semantic level. We calculate cosine similarity scores between all pairs of characterizations of an entity. For those with similarity ≥ 0.7, an invisible edge is added, which acts in the physics simulation of the graph, pulling the two characterization nodes closer together the more similar they are.

Moreover, for an entity pair (A, B), characterizations of A might occur in tweets with only A, or in tweets where both A and B appear. Thus, each characterization is also scored with the ratio of how often it occurs when A is in the context of B, weighted by how often A itself occurs in the context of B out of all its occurrences. For a given characterization c of entity A, let c_{AB} be the number of times it occurs in tweets with both entities A and B, and c_A the number of times it occurs in tweets with just A. Let t_A be the number of tweets with only A, and t_{AB} the number of tweets with both entities, then we calculate this score r_c as:

$$r_c = \frac{\frac{c_{AB}}{c_A+c_{AB}} * \frac{t_A+t_{AB}}{t_{AB}}}{\frac{c_{AB}}{c_A+c_{AB}} * \frac{t_A+t_{AB}}{t_{AB}} + \frac{c_A}{c_A+c_{AB}} * \frac{t_A+t_{AB}}{t_A}} \tag{2}$$

This score is used to indicate whether a characterization of A is more likely to occur in the context of the second entity B than would be expected based on the relative frequency of the two entities, based on which the characterization nodes are coloured.

2.4.2 Relationship Pathways through Tweets. We propose that the dependency tree form of a sentence encodes the relationship that the author describes between them in a structured form, which can be visualized in the graph view as a path connecting the two entity nodes through a number of words. The predicate of a sentence is at the root of its dependency tree; predicates of subclauses are children of this root verb. From there, there are three possibilities of how the two entities can appear in one sentence in respect to each other:

- one entity is the subject executing the action, the other the object that is being acted upon
- both of them are objects of the same action
- the two entities belong to different subclauses

The shortest path between the two entities in the dependency tree (converted for this step to an undirected graph) then provides a path connecting the noun phrases of the two entities via that part of the text that is pertinent to their relationship. If one of the entities is the subject of its clause, then by switching the direction of edges between a verb and the noun subject, the path can be followed from the subject via the verb to the object; or in the case of more complex relationships through a relative clause to the entity in that clause. In the example shown in Figure 1, the path is very simple: (Inflation) −> (causing) −> (Economic inequality).

From all the tweets that mention both entities, all unique relationship paths are collected, and those seen only once are removed. The remaining paths are consolidated to combine partial paths shared among different relationships: The nodes are numbered from the centre of the path, that is, the node from which all edges are outgoing. Only those edges with two identical incident nodes both in the text and in the index of these nodes in the path are combined into one edge.

2.5 Filtering on Tweet Meta-Data

The filtered view of the big picture network presents a general overview of the inequality discussion on Twitter during the time from which we collected the corpus (2020-2022), showing the most

[3]These static vector embeddings have been shown to provide a useful representation of word meaning and preserve relations between different words in their relative position in the vector space. In contrast to more recent language models, static embeddings are consistent for unique words independent of the text in question; so that the same term as it appears in different tweets will be represented by the same numerical vector.

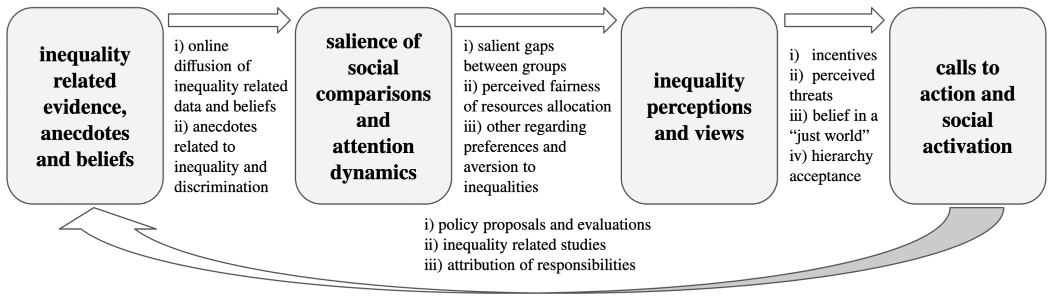


Fig. 2. A framework of the impact of inequality through common discourse on social media.

important and most commonly co-occurring entities. Alternatively, it is possible to filter based on the characteristics of the tweets themselves. Thus, the occurrences of entities can be limited e.g. based on the location, the number of likes or retweets, or the account's verification status. We analysed the changes in the network throughout the given time period by filtering the entities' occurrences based on the time-stamp and constructing subgraphs for individual months. From these subgraphs, spurious connections (edges with weight 1) are removed, but no further filtering is applied. Each subgraph is also clustered using the Louvain Algorithm.

3 CASE STUDY: INEQUALITY

Studying the public discourse about inequalities is important to understand how these are perceived, described and faced by different groups in different countries or contexts and to map how these views are redefined across time in relation to events, policies and collective actions that may reshape people's attention and aversion to specific forms of inequality. Analysing the public discourse is also key to understanding advocacy actions and citizens' demand for policies [3] aimed at reducing specific inequalities. For example, during the COVID-19 pandemic attention towards education inequality increased [27]. Similarly, after the murder of George Floyd, there has been a growing demand for public action and policies for reducing those inequalities that are disproportionately affecting ethnic minorities [35]. Besides its theorised, material and social implications, like its effect on economic growth [5], discrimination and related inequalities may indirectly harm also the ones that may derive some material benefits from having a privileged position in an unfair society [40]. Concerns for socio-economic inequality that are expressed through social media often go beyond preferences for wealth (re)distribution and for equal opportunities, extending to people's life and work activities and motivation, self-perceived identity and social role, sense of belonging and willingness to cooperate and reciprocate altruistic behaviour in the socio-economic systems in which they operate. Figure 2 summarises the framework we have developed as to how perceptions of inequality and the narratives built upon them are able to shape, through the medium of social media discourse, public policy, and ultimately impact beliefs about inequality as well.

The mere feeling of living in an unfair society can produce a widespread psychological and social malaise and a generalized sense of injustice that may reduce one's willingness to cooperate and trigger the emergence of social tensions, polarisation and partisanship, which can lead to further discrimination, societal conflicts, uprisings and revolts. Therefore, tools that allow researchers to assess almost in real time the attitude of people towards material or immaterial differences between groups are important for both research and policy making purposes.

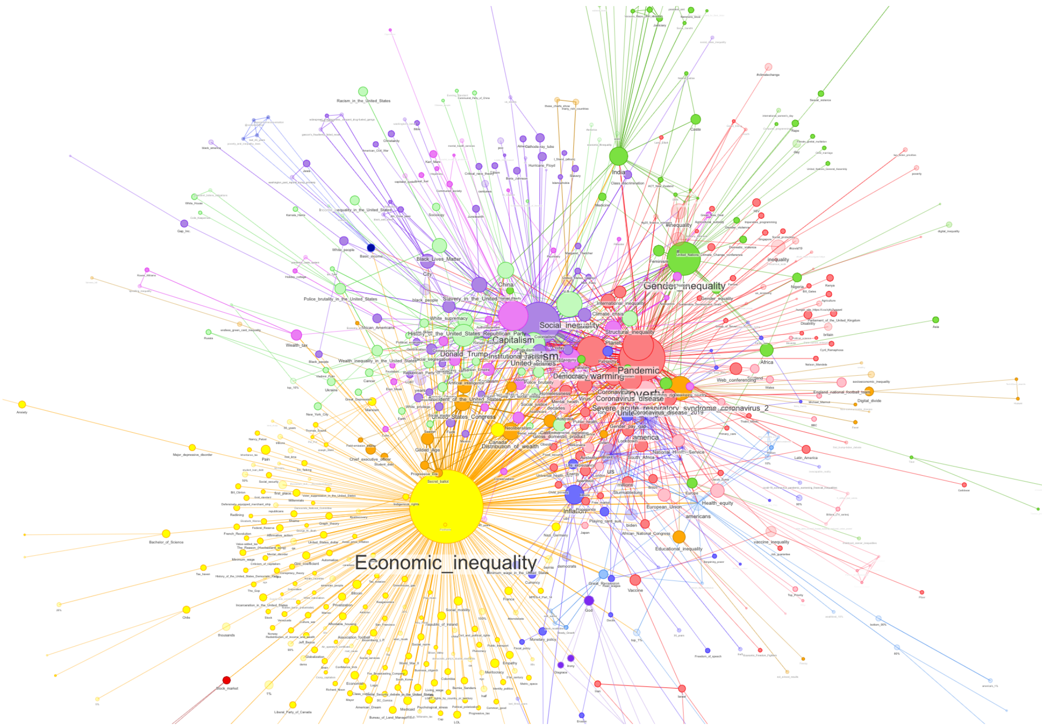


Fig. 3. The filtered bird's-eye narrative network of inequality. Colours indicate clusters. Node size indicates the number of occurrences of the entities on a logarithmic scale. The layout of the graph was calculated using the force-directed layout algorithm.

3.1 Bird's-eye Network

3.1.1 Entities and Co-Occurences. The unfiltered bird's-eye network contains 73901 nodes (unique entities). However, 81.9% of these entities occur only once in the entire dataset. The mean number of occurrences per entity is 2.727 (SD = 46.172). The four most commonly occurring entities are four concepts related to inequality: *economic inequality* (10139 occurrences), *poverty* (3874 occurrences), *racism* (3217 occurrences) and *gender inequality*; which the fifth most common entity being the *pandemic* (1705 occurrences), which is closely followed by *global warming* and *Capitalism*.

Out of all those pairs of entities that co-occur together, most (87.9%) only co-occur once, leaving 9307 entities connected by 19132 edges after the first filtering step. Those pairs of nodes that co-occur most frequently usually include very frequently mentioned entities, with a few exceptions: Among the top nine strongest connections, the ones that include entities not among the most frequent ones listed above are *economic inequality* and of: *Donald Trump*, *Capitalism*, *gilded age* and *inflation*. The next three most frequent co-occurrences include a triple of two terms and a hashtag that do not appear very frequently in general, but that always appear together: *campaign finance*, *gridlock* and *#fixcongress*.

Figure 3 shows the filtered bird's-eye network[4].

[4]We attach interactive HTML files of the bird's-eye network and the fine-grained graphs in the supplementary material. There, smaller nodes can be explored in more detail, and the clusters can be selected individually. After review, these graphs will also be available in our repository.

3.1.2 Types of Nodes. Through the connection to the existing KGs, the general knowledge available about each entity can be accessed, such as the type of the entities. However, as DBpedia collates information from many sources, there are many entities for which several different type classifications are available (following e.g. OWL, Schema, Wikidata, DBO, etc.), and others for which there is only the top-level OWL class "Thing" (which includes all entities which can be considered "things" or "concepts", e.g. *sexism*, *coronavirus disease*, *stock market*, or *podcast*).

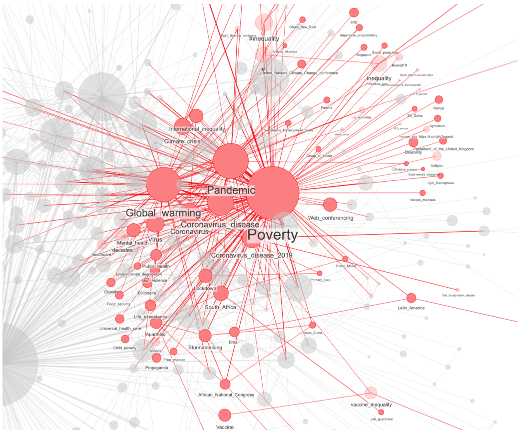
Next to this largest group, there are among those entities which co-occur at least twice: 1910 persons, 1271 organizations, 1362 places, 70 events, 69 languages, 157 mass media channels (television/radio stations and websites), 50 things considered products, and 50 sports teams. The last group is usually a mismatch: mentions of smaller countries are matched to the DBpedia entry of this country's football team. Similarly, there are a number of music albums or other entertainment media - however, in these cases, it is often a phrase that is the title of a piece of media and was incorrectly matched (e.g. "status quo"). We noted that many events were only captured as NP entities and not linked to DBpedia.

3.2 Analysis by Cluster

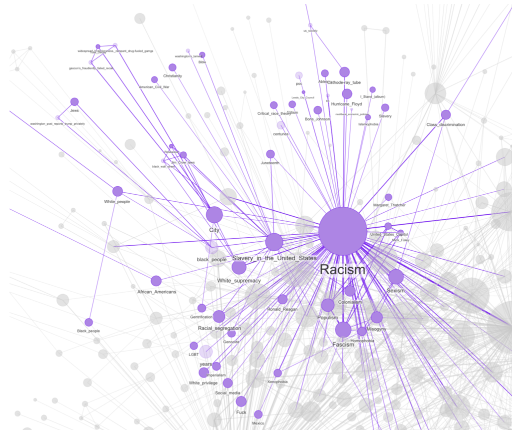
The clusters are derived from the structure of the network. They do not show which entities "belong" to the same topic semantically, but rather which entities are most strongly discussed in connection to each other. Therefore, there are often instances, depending on the filtering, where two apparently different topics (e.g. *racism* and *gender inequality* or the *pandemic* and *poverty*) belong to the same cluster, as well as instances where terms referring to the same overall topic (e.g. *pandemic*, *coronavirus coronavirus disease 2019* and *severe acute respiratory syndrome coronavirus*) are each at the centre of their own cluster.

The bird's-eye network is divided into 17 clusters. The seven largest of these are:

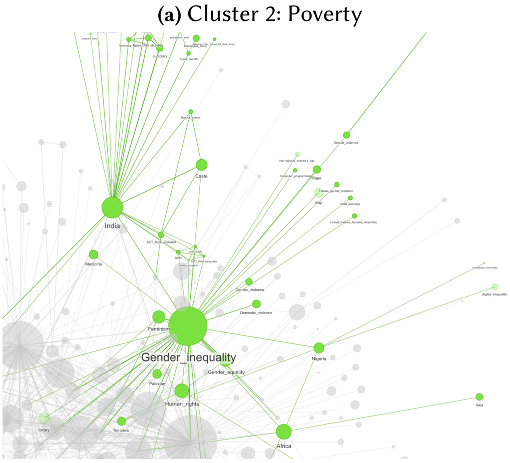
(1) 164 (mostly small) nodes surrounding *economic inequality*. The vast majority of the nodes in this cluster are not or only weakly connected with other areas, with only 6 of them having a degree >= 3 in the filtered network.
(2) 87 nodes surrounding *poverty*. This cluster also contains some of the other largest nodes of the network, which are strongly interconnected and thus not split into separate clusters.
(3) 63 nodes surrounding *racism*. The smaller nodes are not all linked to the central concept but rather form smaller cliques inside this cluster.
(4) 53 nodes surrounding *gender inequality*.
(5) 45 large-ish, sparsely connected nodes which are not so much connected to a central topic as they are descriptive of political concerns in the United States. These include (as the largest node) *social inequality*, *Donald Trump*, *China*, the *Republican Party*, other American politicians, as well as political and social problems which are here discussed specifically in reference to the United States (*police brutality in the U.S.*, *wealth inequality in the U.S.*, and the group *Black Lives Matter*).
(6) 37 nodes including *capitalism*, *democracy* and the *planet*.
(7) one noticeably thin and sparse cluster of 30 comparatively large nodes, which appear situated in between other very frequent entities. This cluster can be visually divided into two sides, one containing *SARS-CoV-2*, the *digital divide* and *educational inequality* (close to the cluster on poverty and the pandemic), the other containing *inflation*, *distribution of wealth*, *progressive era*, as well as the American *president* and *congress*. The reason why these entities co-occur often enough to make up their own cluster appears to be that they occur more frequently in a common interval of time: around the most recent election in the United States. Thus, in



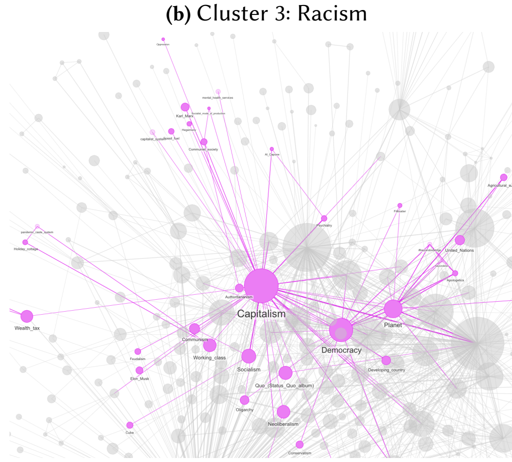
(a) Cluster 2: Poverty



(b) Cluster 3: Racism



(c) Cluster 4: Gender inequality



(d) Cluster 6: Capitalism

Fig. 4. Examples of four of the clusters in the bird's-eye narrative network. Pictures have been cropped to show more details. However, the relative sizes of the four pictures are the same.

this case, the part of the narrative identified in this cluster provides a perspective of a point in time.

Figure 4 shows four of these clusters, three of which focus on a specific reason for or axis of inequality: poverty, racism, and gender inequality. All three of these clusters include several larger nodes or stronger internal connections, as well as smaller surrounding entities.

The cluster on *poverty* (2) also includes the *pandemic* and *global warming*. Many of the smaller nodes in this cluster refer to issues of health in relation to poverty, such as *public health*, *vaccines* and the *Lockdown*; as well as *life expectancy*, *obesity*, *disability* and *mental health*, but also *homelessness* and *gun violence*. Very close to it with many edges connecting them is the *gender inequality* cluster (4). This includes many names of countries and regions, with a focus on the global south. In addition, different forms of sex-based inequality or sex-based violence are linked to other clusters: *domestic violence* is strongly connected to the COVID pandemic, while the topic of *medicine* mediates between this cluster and the one focused on *capitalism*.

Cluster (3), which surrounds the concept of *racism*, has some internal cliques. These show focused discussions surrounding topics such as the history of *slavery in the United States*, or *gentrification* in cities; and recent political events such as the murder of George Floyd and the storming of the U.S. *Capitol*; as well as the relations between different forms of oppression/discrimination (*racism*, *sexism*, *misogyny*, *homophobia*). The comparatively sparse cluster around *capitalism* (6) includes mostly nodes also connected to large nodes elsewhere: concepts such as *socialism*, *neoliberalism*, *oligarchy*, and even *feudalism*; illustrating the point of view from which capitalism is discussed here.

3.3 Changing Narratives Over Time

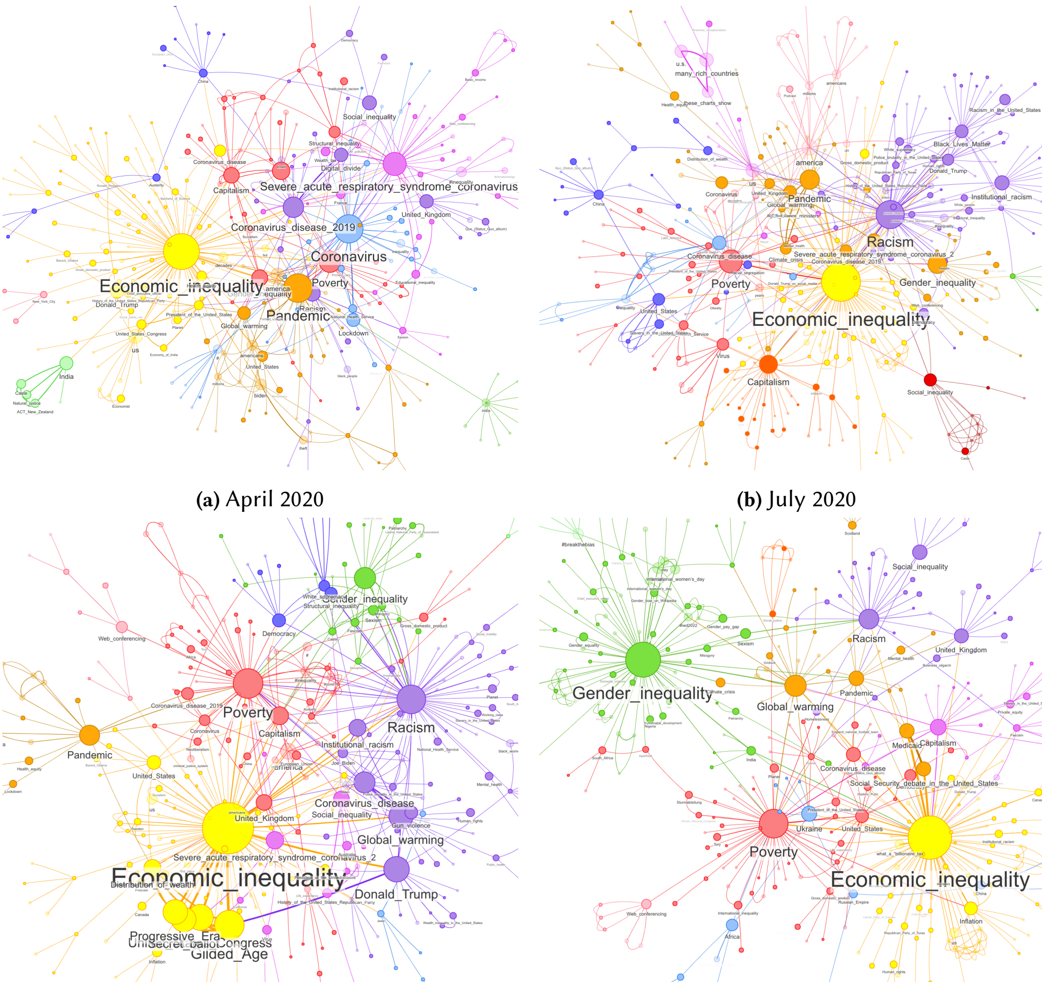
We explored subnetworks for each month and identified periods of interest shown in Figure 5.

3.3.1 The COVID Pandemic. As Figure 5a shows, the biggest topics of concern were economic inequality and poverty, and the pandemic. The latter takes up much of the network so that it is split into distinct clusters (blue, orange, purple, and pink). These entities are discussed in different contexts and thus tend to create a cluster with other entities more commonly mentioned in this context. "The pandemic", "COVID", or "coronavirus" appear to be used more heavily in informal discourse by non-experts and when the topic is not medical, while official information channels, medical experts and scientific discussions tend to employ more formal phrases. Clustering the network can thus distinguish between narratives that impact or are shared among different social groups. In the context of the pandemic, the move to remote work also brought the *digital divide* to the forefront, showing how groups are affected differently and how existing inequalities are exacerbated by such crises.

3.3.2 Black Lives Matter. In June 2020, protests broke out across the United States under the banner of "Black Lives Matter" after the killing of George Floyd. In Figure 5b, the purple cluster is subsumed by the subnetwork on racism, and the COVID pandemic now makes up the orange cluster. The largest increase in the number of related tweets was in June, and by July, the size of the subnetwork has returned to a level comparable to April. Yet, the discussion surrounding racism has not disappeared and will persist in the future, showing the lasting effect of this event in highlighting inequality related to racism.

3.3.3 The 2020 United States Presidential Election. Social media discussion on the U.S. election was widespread in October 2020, and in many cases, issues of inequality were mentioned in this context. This is one case where different topics are contained in one cluster (racism, global warming, the pandemic, etc in the purple cluster). It appears that here, these are more commonly discussed together, and there is more focus on how they impact each other. This is also the only month in which the economic inequality cluster contains more than one large node: *America* and the *U.S. Congress*, and a number of phrases ("gilded age", "secret ballot", and "progressive era"). Clearly, the issue of economic inequality was perceived to be an important factor in deciding the outcome of the election, which is also evidenced by the fact that the cluster of poverty (red) is much larger than before.

3.3.4 International Women's Day. At the end of the two-year period, in March 2022, COVID-related concepts have become tangential to other issues. There is less connection between clusters, with conversations around gender inequality (green), racism (purple), global warming and health (orange), poverty (red) and capitalism (pink) all separated. A new cluster includes Ukraine and Russia (light blue), due to the invasion of Ukraine in February 2022. Otherwise, this month is dominated by the discussion surrounding gender inequality, as March 8th is International Women's Day.



(a) April 2020

(b) July 2020

(c) October 2020

(d) March 2022

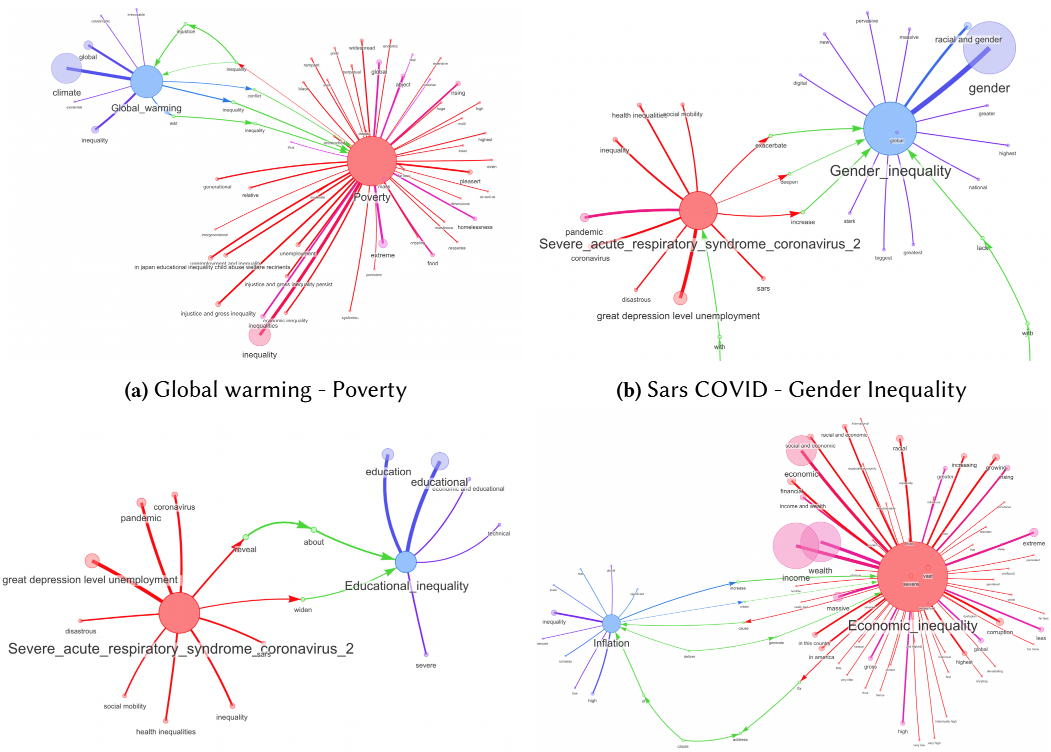
Fig. 5. Examples of four of the clusters in the bird's-eye narrative network. The images have been cropped to improve the readability of the node names (only names of larger and, thus, more frequently occurring entities are shown). The relative sizes of nodes across the images are preserved, meaning that the changes in the size of a particular node represent it appearing more or less frequently in the respective months.

3.4 Fine-Grained Analysis

Figure 6 shows four examples of the fine-grained network[5]. We picked one more general example (*global warming in relation to poverty*, two cases related to the COVID pandemic (gender and educational inequality), and one example related to a more recent development (economic inequality in the context of inflation).

3.4.1 Poverty and Global Warming. The *poverty* group is much larger, with many descriptions and characterizations. The group of co-located characterizations in the bottom left contains terms

[5]The interactive graphs can be viewed in the HTML files included in the supplementary material.



(a) Global warming - Poverty

(b) Sars COVID - Gender Inequality

(c) Sars COVID - Educational Inequality

(d) Inflation - Economic inequality

Fig. 6. Four examples of the fine-grained analysis. The position and colour of the entities is random. However, the characterizations that surround the entities are coloured to indicate how strongly a given characteristic is associated with the entity in question in general vs with it in the context of the other entity. In the relationship paths, the direction of edges visualized the direction of the relationship from the active to the passive party.

related to inequality. The characterizations of poverty which are more common when it is discussed in connection with *global warming* include "global", "abject", "extreme", and "victorian", as well as "homelessness" and "food". In comparison, the descriptions which are common for poverty without the connection to global warming ("great", "high", "endemic", "persistant", "systemic"; but also "lower") are noticeably less emotional. Similarly, in the context of poverty, global warming is more likely to be characterized as "catastrophic", "irrevocable", and "existential". The network highlights the causal relationship between global warming and poverty, in particular through war and conflict due to climate change. The role of inequality as an intermediary variable between the two is particularly interesting, showing that people also believe that climate-change effects on poverty are catalysed by inequality.

3.4.2 COVID and Gender Inequality. The *SARS-CoV-2* entity is characterized by concerns relating to "health inequality", "social mobility", and "unemployment" – it is not itself described with many adjectives other than "disastrous". In contrast, *gender inequality* is almost exclusively characterised by the adjectives with which it is described, which denote scale ("massive", "stark"), recent increase ("biggest", "highest", "greatest"), and its extent or context ("pervasive", "national", "digital"). More frequent, however, is the characterization of it appearing in a pair together with racial inequality.

The relation paths between the two entities in the network evidence the indirect relation between the COVID pandemic and gender inequality. There is a prevailing narrative that the pandemic has exacerbated, increased and deepened gender inequality. Interestingly, the contagion channels through which this relation produced its effect, such as job losses during the lockdowns disproportionately affecting women, are not mentioned explicitly. The effect that the pandemic has can also be seen in how gender inequality is characterized in this specific context, as the adjective descriptions (such as "massive" or "highest" gender inequality) are all more likely to appear in the context of the COVID pandemic than without it.

3.4.3 COVID and Educational Inequality. *Educational inequality* was not as frequently discussed as gender inequality, and thus there are fewer interesting characterizations. Especially in the context of the pandemic, it is related to economic and technical issues and is described as "severe" more commonly than outside of the COVID pandemic. There is a clear narrative of the COVID Pandemic widening existing education inequalities. This is supported by what we now know of the effects of the COVID pandemic on children's psychological well-being and schooling during the lockdowns of 2020 and 2021 [25, 39]. One important point appears to be the impact of technology and the digital divide in education.

3.4.4 Inflation and Economic Inequality. Between 2020 and 2022, *inflation* has been described as "high", more often than "low" or "lower". It has also been called "runaway" or "rampant", and has been located on a "global" scale more commonly in connection to *economic inequality*. The latter is also characterized by many descriptions of scale, showing a perception of greater economic inequality in the context of inflation. It is connected to "income" and "wealth", but also to racial and gender concerns and is mentioned both in the global/international as well as a local context (focusing on the U.S.). The most prominent narratives connecting the two entities follow a well-known relation between inflation and economic inequality [12, 34]. For example, high inflation for primary goods, like food, tends to disproportionately affect those communities and families that are already economically and financially fragile. Interestingly there is also a link in the opposite direction, that is, economic inequality causing inflation, which is a hypothesis that has little evidence in economic literature.

4 DISCUSSION AND CONCLUSION

In this work, we have implemented the two-phase narrative analysis framework proposed in [32] in a visualization tool that can be used to interactively explore the narrative network. Building on this framework, we show how information from natural language understanding and knowledge representation can be integrated to extend both parts of the analysis.

On the one hand, the general knowledge from KGs can be used to consolidate actors and events that take part in the narratives, making it possible to highlight the different ways in which these entities are viewed in different kinds of narratives and in different contexts. In the future, we hope to extend this narrative exploration tool with more information from knowledge sources. Firstly, by allowing users to access this information directly from the nodes of the network, and secondly, by analysing the KG in order to find "ground truth" connections between two entities that can be compared to their relationship as described in the social media discourse.

On the other hand, the information from social media posts can be used to extend the KG. Our approach identifies NP entities that are concepts not currently captured by the KG but that clearly play an important role in the inequality discourse, such as *vaccine inequality*, *green card inequality* or *student load debt*. In many cases, these terms appear on social media before they are eventually added to more formal knowledge sources. Other terms can be linked to a general concept in the KG but, in fact, highlight a current event, development, or perspective related to the concept: the frequent occurrence of *inflation* or *web conferencing* does not refer to the general concept itself, but rather mirrors the recent increase in inflation or the importance of remote work tools during the pandemic. Linking events to KGs is more difficult than identifying people or locations, as evidenced by the fact that only very few entities in the bird's-eye network are linked to events in the KG. Even though a Wikidata entry regarding the current inflation exists[6], matching references to it is difficult, and the entity does not currently contain a lot of information such as that it is an event in time. However, combining references to inflation from many texts, the characterizations extracted from them, and the metadata of the tweets could make it possible to improve the linking and extend the KG information.

In exploring the bird's-eye and the fine-grained network, one interesting problem related to NER and NEL becomes clear: there are many cases in which ML-based entity linking fails due to the context in which the entity appears, the shortness of the texts and the informal language used on social media. This includes not only vague references to events (which require context about the time of writing to understand), but also: missed links due to informal spelling conventions or shortened names ("us" meaning U.S., "fed" referring to the Federal Reserve System in the United States); frequently repeated phrases relating to concepts ("the status quo") or events ("I stand with ...") being matched to the titles of music albums; entities that share a common name with other, more typical entities, where correct understanding requires the larger context of the conversation[7]; and incorrect links that appear to mirror a perspective on the entity that exists in the language, but influences the linking due to the semantic encoding[8].

In the work presented here, we used the proposed approach to explore the narratives shared as part of the common social media discourse surrounding inequality, specifically during the time period from 2020 to 2022, which was heavily characterised by the COVID pandemic and its socio-economic implications. As the results suggest, Twitter discourses on inequality are dynamic and multifaceted. Sometimes inequality-related claims are based on statistical data, while at other times, they are based on erroneous beliefs, which is why being able to capture and analyse them is crucial for a broader understanding of the phenomenon, its cultural and political implications, and its impact on people's (material and psychological) well-being. The case study presented in Section 3 highlights how researchers' connections of interest can be found interactively and can be analysed in more detail by "zooming in" on a given relation (i.e., edge). Next, we plan to extend this tool and evaluate it together with domain experts. We intend to develop an interface that will allow non-computer scientists to filter the data and retrieve KG information, offering them to perceive the multiple viewpoints of any narrative. At the moment, the presented case study is limited in scale due to the requirements of natural language processing and requests to the KG for entity linking. Therefore, we hope to scale up the architecture to enable new data to be retrieved and processed on the fly, allowing users to continuously observe how the inequality discourse develops over time. While this tool offers a novel approach for assessing and analysing diverse narratives interesting to this community, we hope to reach people beyond scientific fields, such as news media and policy-makers, to observe the bigger picture behind inequality narratives.

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[6]https://www.wikidata.org/wiki/Q110281455, which is described as "ongoing global surge of higher-than-average inflation".

[7]In the training data for the NEL, the names of small countries in Europe likely usually refer to a football team. However, after the invasion of Ukraine in 2022, there was a marked increase in mentions of different European countries on English language social media, without explicit reference to the invasion but clearly understandable to human readers, given the overall context. In this case, NEL could be improved by comparing, e.g. whether the Latvian football team or the country Latvia is closer connected in the KG to other entities mentioned in the tweet.

[8]An example of this case is that they are many occurrences in which NEL links the phrase "russia" to the KG entry of the *Russian Empire* instead of the country *Russia*, often when it is mentioned in the context of aggression or invasion.

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