

Tracking Public Sensemaking through Rhetorical Annotation of Image Memes

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Abstract:

Political polarization and declining trust in institutions are driving societal destabilization and radicalization. Recently there has been increased interest in online misinformation intervention and deterrence, for example through the use of machine learning on language use. We argue that addressing crises in the information environment will require a sharper situational awareness and a deeper understanding of how beliefs emerge and crystallize, as well as greater connectivity in the work of teams and organizations in order to reduce the effects of bias and partisanship in collection and analysis. Image memes play an increasingly important role in public sensemaking and discourse and the emergence of public beliefs. Despite their significance, image memes have proven to be a very difficult category of artifact to collect, classify, and analyze in aggregate. In this white paper, the function and form of image memes are discussed, the challenges of performing image meme collection and analysis within the context of emergent, interdisciplinary teams are detailed, and requirements and recommendations for alleviating these challenges are offered.

A Case for Rhetorical Annotation of Image Memes

A growing loss of faith in normative institutions and official accounts of historical or current events is violently destabilizing social bonds. One of the drivers of this destabilization is a growing divide between those who still grant credibility to institutional narratives and those who have gravitated via social media toward counter-institutional narratives. The rise of counter-discursive online communities has produced shared identities constructed through shared narratives. Recent years have seen the emergence, among social media users around the world, of the “truth-teller” or “digital warrior” identities constituted by the consumption and sharing of counter-institutional narratives [1].

Specifically, counter-narratives are being seeded and maintained through image memes. There are now numerous operational and formal definitions of image memes, sometimes referred to as “internet memes” [2,3]. The newer definitions serve to disambiguate the image-embellished-with-text, ubiquitous on social media platforms, from the more general “meme” originally proposed by Dawkins [4] and further developed by Blackmore [5], Dennett [6], Heylighen [7], and others, referring to any “cultural component passed from one individual to another by non-genetic means, or imitation” [3].

In this article, we focus on the “image meme” format (as seen in Figures 1, 3, 4, 6, and 7), operationally defined as a shareable, digital image that contains either non-textual visual symbols or text or a combination of both. While other media formats (e.g. GIF, audio, video) are also ubiquitous, we focus on the image meme in particular to articulate scalable computational systems for rhetorical annotation and analysis which could enrich current analysis methods such as sentiment, semantic, narrative approaches.

While image memes used to be regarded as ephemeral detritus of the Internet intended primarily to induce humor, the powerful role they can play in the formation of public belief and sentiment is becoming increasingly evident [8,9]. Amidst the voices calling for urgent study of the memetic construction of public belief [10], we emphasize the need to examine image memes for their communicative (rhetorical) function as quasi-arguments in public discourse [11].

We recommend applying the structural framework of the Toulmin model of argument analysis to trace the public argumentation performed by image meme circulation [11]. We advocate the application of an argument framework because image meme content is being widely used to advance claims that appear reasonable, despite minimal evidence presented within the meme. Such memetic content has demonstrated strong potential to shift public belief and spur public action [12]. The Toulminian model identifies three

fundamental components of an argument - claim, evidence, and warrant [13]. The claim refers to the proposition that the audience is being asked to accept. The evidence refers to information that supports the claim. The warrant, often not articulated, refers to each assumption that connects evidence to claim.



Figure 1. Example Image Meme.

For example, rather than dismissing the meme above as intended purely for humor, an audience enculturated to reject institutional narratives recognizes that the meme advances the claim that space agencies such as NASA are engaged in long-term deceit. The meme does this by presenting an argument that can be outlined using the Toulmin model as below.

- **Evidence**
 - **IF** a security camera offers only a grainy image
- **Claim**
 - **THEN** space agencies are lying about images from space telescopes.
- **Warrants** (unstated but implied claims which are already established as true for the audience)
 - **BECAUSE**

- i. We should be able to see someone on a security camera much more clearly than celestial objects in space
- ii. Space agencies have a history of presenting fiction as fact (e.g. faked moon landing, doctored images)

The advantage to annotating memes using an argument framework is that we begin to identify how certain ideas which are not contained within the image meme itself (i.e., NASA is a fake organization) and sentiments (i.e., suspicion toward NASA) propagate across publics. Argument analysis reveals the power that memes have to shape public belief by simulating appeals to logic, even spuriously, by functioning as quasi-arguments. Memes function as arguments when they invite an audience to accept a claim, based on evidentiary information that is sometimes contained in the claim and sometimes implicit. Nevertheless, for an audience to accept the claim, the meme also relies on implicit warrants. Interventional approaches to addressing memetic circulation of misinformation, therefore, need to target, expose, and challenge spurious evidence and hidden warrants that specific memes rely on, in order to induce skepticism toward the memetic form as a mechanism for sound reasoning. Fact-checking articles designed to debunk memes have limited success in dismantling the power of memetic argument, in part because they assume a different rhetorical form. Counter-memes that identify and challenge the argument components of original memes could present a more targeted strategy. However, we advocate strong caution in the use of this approach. Counter-memes should not be used to advance novel competing claims but instead highly purposefully to dismantle already circulating spurious memetic arguments, since the objective of intervention is to challenge reliance on memes for public sense-making.

A rhetorical argument-based approach to analyzing image memes can advance our understanding of their persuasive influence beyond the current practices of syntactic tagging of memes, for example by text recognition [14] or classification of memes into categories based upon visual similarity. Previously, we have argued that a rhetorical approach fills in the gaps endemic to tagging practices by enriching analysis of image memes with rich semantic information embedded in the parsimonious combination of the meme components [15]. While in recent years, small-scale rhetorical analyses of image memes have been published [16], these methods have not been implemented widely.

Much attention has been paid to specific large-scale shifts in public beliefs, such as vaccine rejection [12], COVID denial, and rejection of various global election results. However, we argue that what deserves more attention in academic, political, and security analyses is a focus on the underlying common thread running through these far-ranging belief and

attitude shifts, namely the mechanism of change: the creation and maintenance of shared beliefs, and the provocation of shared emotions through memetic persuasion [15,17–21].

Despite legitimate concerns about the degradation of public information due to the infusion of spurious counter-institutional content (e.g., “fake news” and misinformation), we argue that viewing the information crisis as a competition between truth and falsity obscures the nature of the digital information crisis we are facing and, worse still, hampers efforts to restore trust and rework social consensus. Framing the information crisis as a battle between true and false information has not proven effective in regaining the trust of those disaffected by mainstream channels of information. A simplistic true/false dichotomy ignores the complexity inherent in counter-institutional narratives and furthermore prevents us from studying the rhetorical conditions that enable the subversion of mainstream narratives by competing ones. Deploying this dichotomy through strategies such as fact-checking pop-ups that overlay memes on Facebook can actually undermine the ability of good-faith actors to either correct or contribute to competing narratives. Those who seek to address our information crisis will need to do more than target and neutralize alleged sources of misinformation - they will need both a deeper understanding of how beliefs emerge and crystallize, and a sharper situational awareness.

The scale and rapidity with which emerging political and social events are being co-opted into counter-narratives is possible because of the extreme parsimony and virality of memetic argument. Since the split between institutional and counter-institutional narratives has solidified as a social schema, emerging events create a vacuum into which counter-institutional content can be introduced. This content, in image memetic or other forms, has the capacity to nudge social actors into rejecting institutional narratives about events and can reinforce the rejection of political, corporate, and social institutions. Therefore, information systems for large scale analysis of memes as persuasive artifacts are urgently needed. Such information systems have the potential to provide early indications and explanations of shifts in public belief and attitude, which can then be measured with more sensitive and reliable tools. While there are tools which offer operational situational awareness related to sentiment in text-based artifacts [18], image memes have proven to be a very difficult artifact to collect, classify, and analyze in aggregate and there are no standardized practices or appropriate tools for this process. Even outside the context of analysis, no viable and accessible methods exist for systematic search or collection of image memes.

Accordingly, in this article, we build on previous work that proposed a computational framework, combining rhetorical analysis with an ecosystem approach (see Figure 2), to

trace the ebb and flow of narratives through memetic circulation across digital publics [15]. We first provide background on the rhetorical form and function of the image meme. We then offer a set of vignettes to communicate the challenges practitioners face in collection and analysis of image memes, and to explore what tooling and related capabilities would alleviate these challenges. Finally, we provide recommendations for developers who are working on related technologies and those who may be interested in providing the necessary infrastructure for an ecosystem-approach to enable situational awareness in the (mis)information environment.

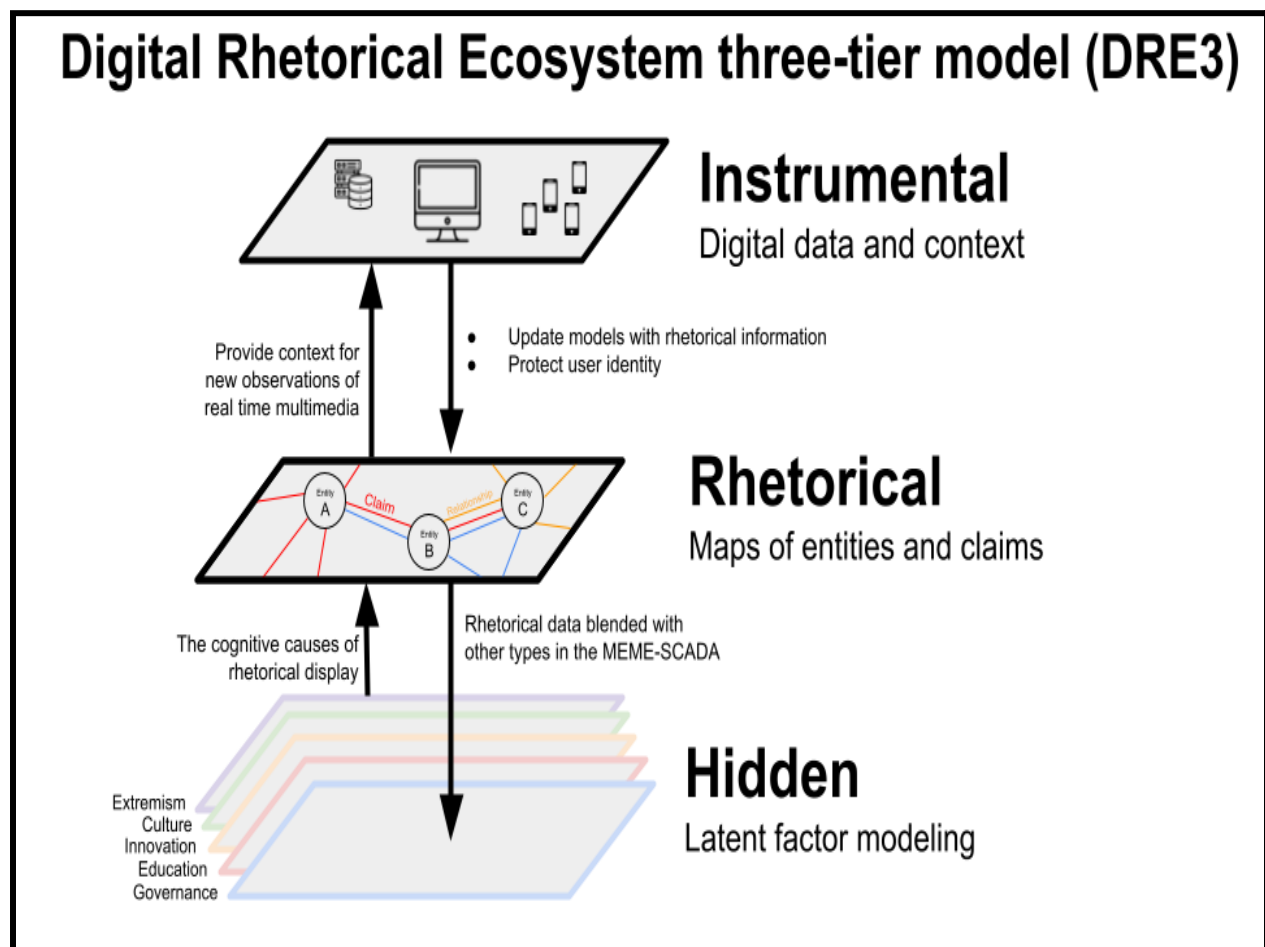


Figure 2. Digital Rhetorical Ecosystem three-tier model (DRE3), from [15].

Elaboration of the Rhetorical Form and Function of Image Memes

We can consider image memes in terms of two complementary features - form and function. The form of the image meme is established by the rectangular box frame which circumscribes one or more rhetorical elements, demarcating the meme as a discrete communication unit on platforms like Facebook, Instagram, and Twitter. While image memes perform a variety of rhetorical functions [22,23], we restrict our attention to image memes that play a particular rhetorical role by participating in public argumentation by advancing claims [24].

Although image memes can be circulated to drive any narrative online, they have marked success in the disruption of official narratives across the political spectrum [9,12]. Their truncated or compressed form is well-suited to inject targeted challenges to mainstream claims. The parsimonious form of the image meme provides great capacity for semantic encoding to advance persuasive claims while diminishing burdens of proof and elaboration that other rhetorical artifacts, like news articles, would require (or be expected to provide). Various image meme formats exist, such as text-only, image-only (no textual elements), screenshot, and image-text juxtaposition. These varied formats, and combinations among them, can create polysemic affordances [25]; that is, they create the possibility of extracting multiple and multi-layered interpretations within a range of meanings. The strategic ambiguity inherent in memetic artifacts allows for rich semantic encoding. At the same time, the structural features of the memetic form (i.e., the containment of its content in a box, and the text/image syntax) strategically constrain meaning-making by setting up the key elements of an argument and cutting off counter-arguments. Below, in Figure 3, we illustrate the argument development contained in one sample image-text meme.

Figure 3 constructs an argument with the simple juxtaposition of two lines of text above and below a stock photo. The choice of the photo combined with the double textual framing relies on the contextual knowledge of discursive communities to decode the argument. While the explicit memetic content is sparse, its signifying layers are rich, thus allowing the meme to advance a clear and persuasive claim.

The primary claim distilled from this image-text meme is that the official masking policy to combat the virus is not to be trusted. The rhetorical power of the meme draws from its strategy of juxtaposing two official narratives that appear to be mutually exclusive - that is, if the virus is virulent enough to escape the strict safety protocols of a world-class laboratory [evidence], then ordinary masks should be ineffective [claim]. The implied

warrant in this case is that both statements cannot be true at the same time, which evokes the broader warrant that official accounts of the virus's origins as well as official policies to combat the virus must be false. The meme simultaneously alleges dissonance in official claims and expresses a disdain for those who accept the official narratives and are oblivious to the dissonance. The meme carries both content designed to appeal to audiences' logical reasoning as well as to activate an emotional charge in the audience. The logic and emotion evoked by the meme are abetted by the meme's use of the "Condescending Wonka" image deployed memetically since 2011 to convey patronizing sarcasm [26].

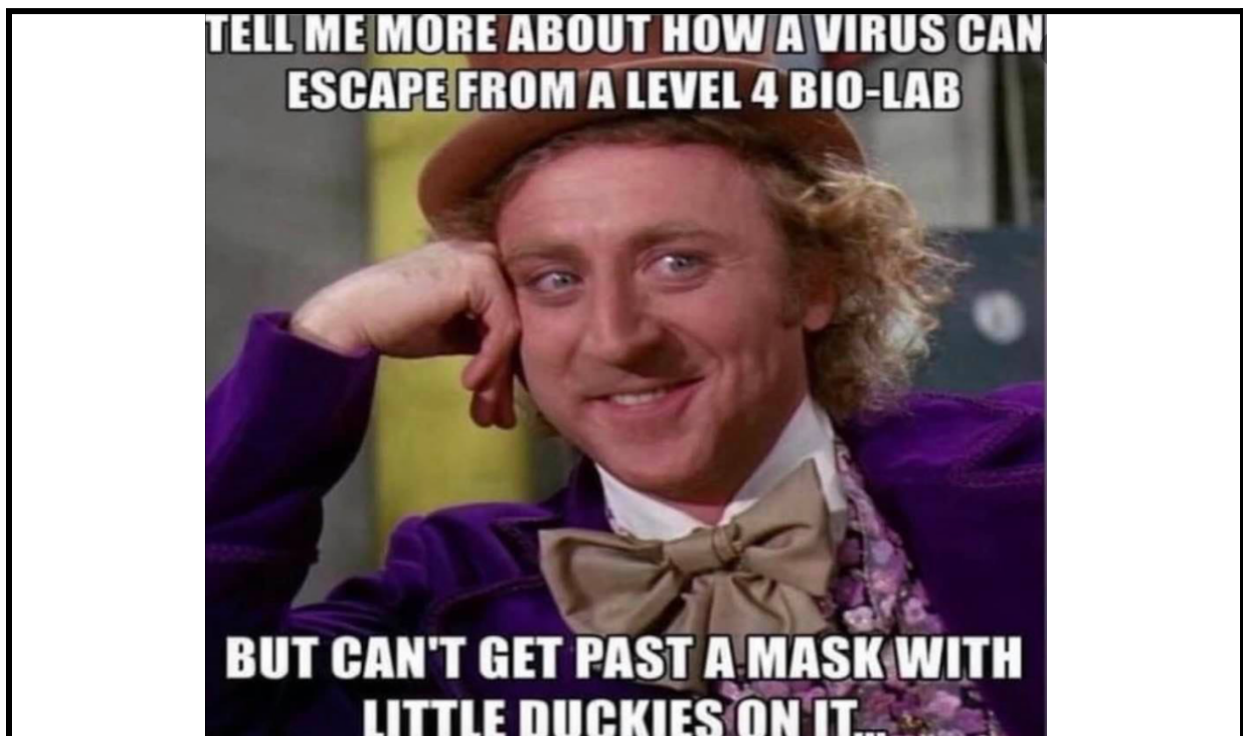


Figure 3. "Condescending Willy Wonka" image meme.

The two lines of text interspersed with the image interpellate an audience into the persona of Condescending Wonka, questioning not only the official COVID-19 narratives but also the intelligence of those who have not yet figured out the contradiction. The meme positions the audience that agrees with its claim on one side against lying officials and people that trust official narratives on the other. The rhetorical deftness of this particular image text meme lies in its ability to swoop an audience, in the course of a single engagement with the meme, into both the line of reasoning set up by the meme and into an interpellated audience identity. Even as viewers might be encountering the meme's reasoning for the first time, having followed the reasoning and accepted it, they come to embody the persona of the one questioning the official narrative and distinguishing themselves from

those who don't. The semantic decoding effort demanded by the meme works to enhance the credibility of the meme's claim by interpellating audiences as truth-discoverers. By advancing claims, memes not only shape public beliefs but also constitute powerful rhetorical audiences, knitting together discursive communities that share memes and bond over decoding and accepting memetic claims.

The boundedness of the image meme above (i.e. its containment with the rectangular box frame) and the parsimony of the rhetorical elements within the meme inhibit central processing and encourage peripheral processing of the meme's claim [27]. The particular rhetorical form of the meme thwarts further questioning into possible reasons why the two supposedly contradictory claims may, in fact, not contradict each other. The success of the meme's argument relies on the implicit warrant that the virus's escape from a protected lab and the possibility of a mask protecting the wearer from the virus are mutually exclusive. The possibility that initial spread was virulent because the virus encountered an unsuspecting maskless population is elided by the memetic structure. Likewise the claim that masks only mitigate but do not necessarily prevent infection is also obscured by the certainty evoked in the meme's juxtaposition of claims. Image memes often simultaneously function as assertive yet weak arguments. Their weakness lies in the fact that their parsimonious form limits elaboration, specifically hiding warrants. However, the parsimony is also responsible for obscuring the weakness of memes. The limited information, visually bounded by the meme's rectangular box, seals a particular conclusion while deflecting attention from warrants that could challenge the meme's claims.

Given the rhetorical power of meme circulation, as elaborated above, to shape public belief, opinion, and sentiment at this time, we urge large-scale collection and analysis of memes that circulate via social media. The ethics, legality, and implications of collecting social media information are a complex and fraught issue, beyond the direct scope of this article, though we discuss some related aspects. Importantly, we have argued previously that personally-identifying information is not necessarily required in collection and analysis of memes [15], elevating privacy protection to a key concern.

Collection and analysis of image memes at scale pose numerous unprecedented challenges that current practices are ill-equipped to meet. This effort will require teams that are curated and structured for efficient and optimal analytical outputs. In the next section, we outline the obstacles that collection and analysis teams are likely to face and, accordingly, recommend practices for structuring such teams, their processes, and outcomes.¹

¹ Outcomes might include situation reports, research products, actionable intelligence, or stewardship of artifact collections for posterity (e.g., the world's largest meme museum).

Limitations on Artifact Collection by Emergent Teams

Presently, the process for collecting image memes and similar “artifacts” [28,29] for analysis of social narratives, sometimes referred to generally as “artifact collection”, depends almost entirely on the community or communities involved. There are limited best practices, no use-case specific tools, and collection is performed in a wide variety of contexts, sitting at the intersection of myriad fields, including advertising, rhetorical analysis, information operations, misinformation response and intervention, and cognitive security [18]. Given both the plethora of approaches and stakeholders, and the complexity of the phenomena they seek to address, traditional organizations find it difficult to meet objectives in the absence of cooperation with other groups or reconfiguration [18,30]. As such, it is often the case that interorganizational or interdepartmental teams emerge to perform collection and analysis. Here we consider the state of the art for performing analysis of image memes at scale by emergent, interdisciplinary, interorganizational teams seeking to understand the patterns of public discourse around current events. Specific examples below illustrate how memetic analysis can reveal widely-shared public beliefs and opinions on the ongoing Russo-Ukrainian War.

Teams that intend to engage in image meme analysis may follow myriad paths in pursuit of their goals. Below, we offer an overview of the archetypal phases encountered by three common approaches to image meme analysis undertaken by emergent teams, based on the experiences of the authors. The three approaches are listed in order of increasing refinement of methodology and intensity of resource use (time and computational). The three approaches, referred to as **Haphazard Collection**, **Methodological Collection**, and **Automated Collection and Analysis**, are each accompanied by a description of recommended capabilities and affordances which would alleviate their respective pain points (summarized in Tables 1, 2, and 3).

Haphazard Collection

An emergent team seeking to perform memetic analysis will generally begin its journey through haphazard collection and sharing of memes over some common channel. In the worst case, sharing occurs over email. However, even in the best case, sharing often occurs over an asynchronous chat platform with affordances for setting specific communications channels (i.e., Keybase, Signal, Discord, or Slack). Given that no current tools offer low-code out-of-the-box capabilities for assisting in multi-modal media collection beyond offering storage, the onus is on the organizers and facilitators to expend extraordinary effort to set standards, maintain norms, and motivate members, in order to transform haphazard, general discussion into an artifact collection pipeline. Paradoxically, the social enforcement

of such standards and rules too early can be demotivating and reduce enthusiasm for contribution, effectively requiring a forward-thinking group to choose between losing most information from early collection efforts by not strictly enforcing input standards or risking demoralization and reduced engagement by doing so. It is here that many emergent teams will experience mission drift, a slow process of disintegration, or illusory progress in the form of discussion and collection without definable utility or outcomes.

A team that fails to formalize a methodology will rely on haphazard collection by default and may go through the following stages and challenges (summarized in table 1):

Initial Enthusiasm. As image memes flow in, the team calibrates a common situational awareness of the information environment through discussion, links to the locations where images were found, and informal references to the events and entities which the images reference explicitly or implicitly. This common situational awareness paired with the social bonding over a shared sense of purpose can create a broad enthusiasm resulting in bursts in collection activity that attracts new members. However, this initial enthusiasm requires organizers and those most committed to the work to now have to focus their attention on onboarding, administrative “housekeeping”, and moderating discussion in order to keep the group’s focus on collection.

Internal Disruption. Relevant to discussion of this stage is a design principle in engineering, referred to as “separation of concern,” which is described as the adequate isolation of concerns, documentation, and objectives of each system component, such that the component can be error tested and distinguished from the other components with which it interacts [31]. While at the implementation level this design principle specifically refers to functions and blocks of code, at a conceptual level it has been recognized for use outside of engineering domains in guiding design granularity and modularity to improve operational reliability, collaborative productivity, or process visibility [31–34].

Teams often attempt to implement a separation of concerns through the use of multiple communications channels. However, the lack of collection-specific affordances in the chat platforms in-use means there is often an intermixing of unstructured discussion, structured comments, and collection activity, as well as non-mission focused activity such as professional networking and sharing of unrelated

materials, all in the same spaces. This leads to miscommunications and disruption in collation of relevant objects. Given the subjective nature of image memes themselves and the viscerally emotional states they may provoke, no separation of concern between collection and analysis activities can induce political and operational schisms within the team. These schisms do not simply re-enact broader social dynamics within the group, instead, they introduce rhetorical divergence that can induce cascading organizational failures. For example, difference in opinion can lead to bifurcation (i.e., professional relationships, friendships) even though variation in perspective on that same issue might be tolerated by a political party or company (which may have sufficient size and mechanisms for maintaining organizational coherence).

As a practical example, consider a team seeking to understand the discourse around the ongoing Russo-Ukrainian war which has collected an image meme referencing Nazi ideology in relation to Ukrainian para-military groups (see Figure 4). The intentional or unintentional strategic ambiguity embedded in the meme means both the quality of the claims and the claims themselves, are in the eye of the beholder. Thus, the team's own diversity of perspectives, without high levels of cognitive security and trust, becomes a complex threat surface [30]. One member might interpret the meme in Figure 4 as a reference to Facebook's reversal of content moderation policy regarding the Azov Battalion, which, prior to the war, had been classified alongside other white supremacist groups [35]. However, another might interpret the meme as a mockery of anti-fascist movements in the US and libel regarding the Ukrainian military. Given the difficulty of rapid synchronization of priors, unstructured discussion will almost certainly lead to disagreements in analysis which may expose meaningful, underlying sociopolitical and philosophical disagreements. Where teams lack established affordances, roles, norms, trust, and separation of concerns, there is an enhanced potential for such miscommunications which degrade trust and potentially result in disintegration of the team. Instead, a separation of concerns through tool affordances and role-based access is more likely to ensure that the analytic stage is focused on "trending" rather than "idiosyncratic" interpretations of memetic claims.

Overload. If the team manages to maintain momentum and circumvent tendency toward internal disruption and disintegration, it will next face challenges related to the volume of its collections. Depending on affordances offered by the chat platform in-use, plain-text and links might be exported from chat for analysis or may be searchable. There is rarely a simple method available to teams for the search, categorization, or export of image memes. Even if exported, brute force or manual search, as opposed to query- or attribute-based search, is likely the only method available. This being the case, the more successful the team is at unstructured collection, the less the value of any particular artifact given that the time and effort costs of brute force search increase with the size of collection. Due to this volume-value paradox, success in collections has a direct, inverse relationship with difficulty of analysis.

Lack of Visible Progress. If the team continues operations to collect a relatively high number of artifacts without having resolved separation of concern, search, and collation difficulties through standards setting and compensating controls on inputs - it has likely already undergone some level of "mission creep" or deviation from original goals [36]. As such, the team will likely have no visible markers of progress, which can result in a feedback loop of decreased activity and demoralization of still-active members. If there is no clearly defined process for disintegration or removal of team members based on activity or work requirements, this feedback loop will eventually result in the team ceasing operations as opposed to formally closing.



Figure 4. "Fast Friends" Political Cartoon [37]



Figure 5. Balancing aspects of artifact collection

Methodological Collection

After general, exploratory collection, a team may then formalize their methodology for managing collections. Potential stages and key challenges are described below and summarized in Table 2.

Tool Selection. In order to begin collections, the team must choose a tool for artifact collection, which offers accessible input affordances (e.g., form input) for images and text (e.g., Google Sheets, Coda.io). The larger the team, the more likely it is for conflicts to arise during this process of tool selection. Unfortunately, very few tools in common use have accessible affordances for connecting data such that members could continue using their own tools while being able to collaborate on common digital assets.

Tool Adoption and Configuration. Technical difficulties may occur with adoption and early use of tools or tools may run afoul of organizational security protocols. Moreover, individuals could simply refuse to adopt new tools due to platform or tool overload. Even where members may be using the same platforms already, if members have their own processes or organizational accounts for managing digital assets, difficulties can arise in where and how to store common assets.

During this time, the team may lose members, see a decline in activity and interest, or the team may disintegrate entirely. Poor configuration of the tool's features (e.g., incorrect sharing options leading to inaccessibility) can exacerbate the impact of these challenges.

Maintaining Information Quality. Given a successful migration to a new tool, the team must decide how to set standards for input, such as including certain attributes, links, or other details. Here, the team has to balance the user-experience of the person performing data input with that of the person who will later perform analysis. The more detail that the team requires, the more opportunities for analysis later - but every additional required detail comes with potentially large costs.

Even a very motivated and interested team may see steep declines in activity where input controls are too strict and details required for collection are too voluminous or complicated. Making inputs optional can create an inconsistency that could potentially demotivate

detail-oriented and conscientious team members. Unfortunately, any adaptation will be accompanied by tradeoffs, as the team must balance information quality controls with artifact detail requirements and rate of collection goals, each impacting one another (see Figure 5). Regardless of tool choice, whether or not the team achieves adoption, and the detail of annotation of artifacts, nearly all tools will require the user to switch back and forth between the tool and their browser during collection. This context switching is cognitively expensive, and can result in further declines in information quality and enthusiasm for collection due to poor user experience.

Regardless of scope and controls the team will also have to deal with difficulties in managing duplicates and reducing redundant collections. As the team finds image memes during their collection activities, there is no user-experience friendly method to ensure the item being viewed hasn't already been collected or if the source being accessed has already been searched for artifacts.

In terms of avoiding redundant collections, the team runs into a frustrating challenge. Many of the relevant sources of artifacts are not static web pages, but instead discussion threads that can change over time. Further, the most impactful discussion threads will change rapidly, by merit of their impact. This means the team must risk redundant collections in order to avoid missing new content.

One ameliorating approach is to rely on a "master spreadsheet" or an index to maintain a "single source of truth" for what has been collected and what sources have been searched for artifacts. This process comes with pitfalls that inevitably increase the workload and create inefficiencies. The work involved in duplicate-checking expands with the size of the extant collection of artifacts, making each additional input a contribution not only to the collection, but also to the difficulty of further collections. This constitutes a variant of the volume-value paradox discussed in relation to haphazard collection. Without a means to connect the view the analyst has of the information environment directly to existing collection data, this pain point in analysis is effectively unresolvable.



Figure 6. A collection of image memes; (A) an image meme suggesting one would have to be mentally ill to support Russia's basis for engaging in conflict, (B) an image meme suggesting Russia's handling of protestors is over-aggressive, and (C) an image meme used to represent the status of the relationship between Russia and Ukraine [38].



Figure 7. A collection of image memes; (A) an image meme critiquing profile picture changes in support of trending issues, (B) a photograph of a woman who was arrested by Russian police for holding a blank sign [39] which has been used as an image meme, (C) an image meme suggesting basis for Russian caution in provoking the United States into military action, (D) an image meme comparing Russian and EU negotiation strategy, (E) a screenshot of a subreddit's name and a recent upvoted post, used as an image meme, and (F) an image meme conveying the relationship between Putin and Obama.

Information Integrations and Externalization. As suggested above, maintaining information quality and the level of detail useful for analysis will inevitably come at the cost of the rate of artifact collection. Teams at this stage will often seek to address this challenge by externalizing some aspects of collection, for example, opening channels for input from other teams or the general public, or attempting to integrate already existing collections into their own. Both methods come with challenges. A team which externalizes its collection is now faced not only with processing collected items, but also with managing a crowdsourcing solution, which can be time expensive and unreliable. Attempting to integrate existing collections can be equally challenging, as the likelihood of finding an existing collection fit to the same scope as the team's is minimal, and there is no common standard for image meme citation and collection - creating the need to do additional processing work for relevance.

Further, it is unlikely that these collections will contain any provenance data, which will limit analysis a great deal. The image meme found in Figure 6-C is one such example, where the post in which it is found ties the image to the war through its title, which is not included in the image [38]. Similarly, the image meme found in Figure 7-A might be used in a variety of contexts. Without relevant metadata accompanying entry of these image memes into a shared repository, the team would have to rely on pure speculation to identify them as relevant to the memetic discourse around the Russo-Ukrainian War.

Once again, the team is faced with a fundamental trade-off. If they simply accept a slower rate of collection over attempting to externalize some aspects of collection or integrate from existing collections, the team may quickly run into problems stemming from various forms of bias - as no single team can possibly have all of the perspectives necessary to prevent it.

- Centralization bias may come in the form of collection and analysis tending to have an implicit or explicit overestimation of coordination, rational intent, and common direction or theme [40,41]. For example, the team may see the image memes found in Figure 7-C and Figure 7-D as related to the Russo-Ukrainian War or events leading up to it, even though they were both used in

reference to past events and were picked up in collections that could not be properly scoped by time-of-posting due to limitations on search engines.

- The team's own narrative will inevitably calibrate an informational niche which will create a feedback loop of bias in both collection and analysis activity. This will lead them to overestimate the importance of their own perspectives or of particular narratives relevant to their perspectives similar to "overestimation of our own importance", in the context of intelligence analysis [40], or more generally, a salience bias, leading them to prioritize that which stands out to them as relevant given their prior experiences. For example, consider the image meme found in Figure 7-E, which to some may represent a simple mark of support, as opposed to an argument-by-hypocrisy with relevant connections to other image memes such as the one featured in Figure 4.
- Sample bias will leave the team with blind spots. For example, the image memes found in Figure 3 all feature different individuals and settings. However, all of the individuals and settings featured are from the same sitcom, Parks and Recreation. The team might not be aware of this and therefore fail to mark the sitcom as a referenced entity. These kinds of details may seem inconsequential, but they can be critical for certain kinds of analyses, such as those focused on understanding the demographics involved in generating categories of artifacts, understanding the audience that artifacts were created for, or understanding and discovering coordinated activity. As another example, if the team is unaware of recent arrests of Russian protestors carrying blank signs [39], then the image meme in Figure 7-B (and especially its variations which do not include references to Putin) may not be tied as relevant to the war, but instead as merely a comical exaggeration.
- Additionally, the scope of collections itself may result in further blind spots. For example, the image in Figure 7-B is a photograph, and might not be considered an image meme by an analyst, even though it has been used as one (potentially as a protest-meme against over-moderation). As another example, 7-E is a screenshot,

which, in conjunction with salience bias, may go uncollected despite its previously mentioned potential value in analysis. As a final example, the image in 7-B is now tied to a “copy-pasta” which has spread over Twitter and Reddit:

“A man hands out leaflets on Red Square, and the KGB arrest him. But when they get him to the station, they find that the leaflets are all blank. And he says "Well, everyone knows what the problem is, so why bother writing it down?"

Given that copy-pasta is a text-based format, it would likely not have been considered in an image meme focused collections scope, thus limiting an analysis of 7-B's rhetorical impact. The inability to connect collection activity to the collection activity of other groups with differing scope and collection requirements deprives later analyses of a key factor related to rate of spread and impact of content, and a key indicator of coordinated activity.

Without the ability to modularize, externalize, granularize, and connect aspects of collection to such an extent that it limits the bias of the team's individuals on resulting information quality, biases will likely only be exacerbated by further analysis.

Making Analysis Useful. The team, despite biased collections and challenges in integration and externalization, runs into its final set of difficulties, all related to ensuring the analysis they perform is actually disseminated and of use to others. The problems with rate of collection and analysis means that at this point, any analysis is likely to be a post-mortem of events related to memetic discourse, rather than a map of the current state of a relevant area of the information environment. Of course all analyses are retrospective to some extent, but in the case of memetic discourse, where the state of the environment can shift so quickly - it is likely the case that the information landscape has changed significantly by the time any form of analysis is complete. As such, a team which has been successful up to this point, might simply complete its activities by writing a report or a paper regarding their findings, as opposed to being able to offer any predictive value, actionable recommendations, or situational awareness

to stakeholders. Unfortunately, the value of these information products may be limited to archival or historical purposes unless it had been focused on fundamental research (e.g., understanding mechanism of spread of claims or mutation of image meme format over time). Even the archival value of the work is questionable. While some research work allows value to be salvaged from a project in the form of re-use of datasets, the absence of common standards and provenance data unfortunately means that the generated meme datasets may not be useful to other teams performing similar analyses.

Further, rhetorical analysis of the meaning of image memes is likely to be highly subjective among disparate groups of individuals. This significantly complicates both the process and the resulting utility of the analysis of image memes. Attempting rhetorical analysis may result in unintended, counterproductive outcomes that reinforce the biases of both the team and their stakeholders. A multi-user and multi-community process for determination of rhetorical claims could lend a greater degree of objectivity to the analysis. However, as discussed, these kinds of collaborations face a number of challenges. Focusing on the sensemaking processes of content and semiotic analysis (e.g., "What entities are referenced in this image?", "Are any latent objects signified by the content?"), increases the likelihood of alignment, but this approach is only enabled by well-structured, voluminous collection.

Automated Collection and Analysis

After performing initial exploration of structured collection (e.g. as described above), the team may choose to refine and elaborate its approach towards collecting artifacts via computational methods. This approach generally consists of two primary aspects: Data Engineering and Data Analysis. The challenges of automated collection and analysis can be generalized to those faced in Data Engineering and Data Analysis at large; therefore, a comprehensive discussion is beyond the scope of this white paper. However, some challenges of particular relevance to emergent teams performing automated collection and analysis of image memes are discussed below and summarized in Table 3).

Data Engineering. Depending on the selected data source and desired outcomes, this process could consist of several phases: acquisition, cleaning, formatting, metadata collection, and de-identification.

- **Acquisition.** Data may be directly acquired through a public API (Application Programming Interface) provided by a digital platform, or by scraping memes across different websites and media formats (jpeg, png, pdf, etc). There are various types of API protocols, such as REST (Representational State Transfer) and SOAP (Simple Objects Access Protocol), each of which requires custom connections that vary in terms of difficulty of implementation.
- **Formatting.** Memes should be converted to a common file format for interpretation by a computer vision package such as OpenCV. Image memes may come in any number of sizes and shapes. Therefore, the cleaning pipeline should use uniform resizing parameters that facilitate image and text legibility, and discard memes that do not meet the minimum threshold criteria.
- **Cleaning.** This process can include correcting for errors that occur due to font type and optical character recognition (OCR), removing incomplete files, and potentially removing duplicates depending on the desired outcomes of the analysis. For example, in some circumstances, it may be helpful to understand how many times a meme has been duplicated or how many different groups and/or users engage with a given meme. However, in other circumstances, duplication may bias the results. Hence, the scope of cleaning could entail removing duplicate memes, but will certainly include

removing duplication errors that sometimes occur in the scraping process.

- **Metadata Collection.** Depending on the desired outcome of the analysis, collecting additional data about the source of memes might be important. For example, the team might want to record metadata based on the source of the meme or the date that the meme was posted. When focusing on the flow of information, the user ID corresponding to the individual that posted might be of interest. The team may also want to determine poster demographics (e.g., age, location, religion, political affiliation, level of education).
- **De-identification.** While poster demographics and psychographics can be of value to analysis, some teams may not be able to collect these kinds of data. Moreover, many institutions require IRB certification to use data from human subjects, which always mandates that the subjects are de-identified before the data is analyzed. De-identification can be done by replacing poster names with random variables. However, it is critical to also remove additional demographic information if these data could be leveraged to determine the poster identity (for example only two people over age 60 work at a specific place). These kinds of restrictions can create difficulties for collaborations among teams and limit the applicability of datasets.

Data Analysis. Ideally, the goal of the analysis is outlined prior to data acquisition and is not established post hoc, as it may be difficult to perform specific analyses if the metadata are not properly collected. While there are infinite possible analyses with respect to forum, user, and user demographics, this section will focus on analyzing content that can be found within meme text, meme images, and the juxtaposition of images and text. Furthermore, methods that could facilitate the automated detection of rhetorical claims in image memes, such as functional annotation, categorization, and semiotic analysis will be explored here.

- **Text Analysis.** Meme text has to be extracted through optical character recognition, which converts images of text into

machine-readable text. The semantic content of the text can then be analyzed through any number of natural language processing pipelines, including pipelines for sarcasm detection in memes [42].

- **Image Analysis.** Images can be analyzed for semantic content, such as objects, people, text, scenes, and activities, through any number of image analysis platforms. Gleaning semiotic content from images is more difficult. Recent efforts have attempted to distinguish regular images from image memes [43] and explore the visual semantics of satire [44]. However, we are only just beginning to unravel the complexity of semiotic and rhetorical content embedded within image memes. While manual annotation of memes by humans can be very helpful in creating a training set of data and broad categories of image memes, manual annotation is a time-consuming task with a subjective nature that can yield variable results [45]. Machine learning can reduce the time burden of annotation, and can also be useful for semantic association and classification of images [46].
- **Juxtaposition of Images and Text.** The interplay between text and images in multimodal content can be quite complex, and can have a significant impact on the essence of a meme. The relationships between pictorial and textual concepts and entities are characterized by metrics that include cross-modal mutual information (conceptual overlap) and semantic correlation (meaning overlap) [47]. Moreover, content within images and text can contribute to the rhetoric in the meme in a number of ways. Meaning can be derived largely from the text, as in Figure 3, where replacing the image with any number of images is not likely to interfere with the overarching claim. In other memes the meaning is mostly image-based, as in Figure 7-E; the caption is not necessary within the context of the current Russo-Ukrainian war. Meaning can also be derived equally from image and text, as in Figure 1, where replacing either would significantly impact the underlying claim. The relative importance of images and text has been quantified in a metric called “status” [48]. Deep learning has been used to successfully categorize image-text relationships based on the metrics described above [48].

- ***Categorization of Memes.*** Analysis of the entire memome is as daunting a task as the analysis of the entire genome was at the turn of the 21st century, and we can learn a lot from the successful methods that emerged in the automation of genomic analysis. Automating the ability to understand any meme, from any source, would have to begin with coarse grained analyses (i.e. broad categories) which are then later refined to higher levels of detail (i.e. rhetorical claims). Machine learning methods could be used for meme categorization, with appropriately labeled training data, and the largest and most successful crowdsourced set of manually annotated images and text, Wikipedia, could serve as training data to this end. Wikipedia image and text content is conveniently labeled with category terms that start off at broad levels and become increasingly refined [48]. Wikipedia categories may be a good starting point for the development of categories for a meme ontology, a hypothetical memetic analogue to the gene ontology that is broadly used for functional genomic annotation. Within the memome, there is the potential to uncover memes related to myriad stable and provisional categories. As in the genome, studying the memome will uncover motifs, i.e. recurring patterns with well-defined functions, that belong to categories (usually more than one). For example, based on the images and text, the meme in Figure 4 could belong to categories such as “comic strip”, “Nazi Germany”, “white supremacy”, “Ukraine”, “Russo-Ukrainian war”, “military”, and “hug”. While this level of categorization is far from a rhetorical analysis, it can be useful in the detection of meme types in order to understand the topics individuals or groups are interested in discussing.
- ***Detection of Rhetorical Claims.*** Rhetorical analysis of the claims in image memes is difficult for both humans and computers. Each person brings many years of their own unique prior cultural experience into the analysis of a meme. Computational analysis can benefit from human annotation of rhetoric in training data, although arriving at a definitive claim for every image meme is a daunting task that may have unwanted outcomes (see *Methodological Collection: Making Analysis Useful* above). In understanding rhetorical claims, there are many layers of analysis

that build upon one another. At the most basic level, the concepts and entities present in an image meme are identified. Recognizing entity relationships then facilitates semantic understanding. Automated analysis of memes could be successful to this end; however, sensemaking beyond the semantic level requires a human-in-the-loop to create annotated data. Uncovering latent substance in memes requires understanding the potential alternative significance of the meme's concepts and entities. Although semiotic comprehension can be deeply personal (e.g., not everyone thinks of Grandma when they smell lilacs) there are also signs and symbols that have been broadly adopted. An annotated dataset that links semantics and semiotics would advance our ability to uncover potential latent significance within memes, and advance efforts towards the automated detection of rhetorical claims.

Haphazard Collection	
Stage	Key Challenges
Initial Enthusiasm	<ul style="list-style-type: none"> • No Designated Roles • No Affordances for Structured Contribution
Internal Disruption	<ul style="list-style-type: none"> • No Accessible Tools Designed for Collection Activity or Implementing Related Compensating Controls • No Separation of Concerns • No Role-Based Access • No Affordances for Structured Contribution
Overload	<ul style="list-style-type: none"> • No Affordances for Multi-Modal, Semantic Search • Limited Affordances for Structured Archiving
Lack of Visible Progress	<ul style="list-style-type: none"> • Mission Creep • Lack of Ability to Measure Progress

Table 1. Key Challenges in Haphazard Collection

Methodological Collection	
Stage	Key Challenges
Tool Selection	<ul style="list-style-type: none"> • Tool Overload
Tool Adoption and Configuration	<ul style="list-style-type: none"> • Tool Overload • Lack of Tool Interoperability • Lack of Accessible Connectivity Affordances Among Teams and Platforms
Maintaining Information Quality	<ul style="list-style-type: none"> • Poor User Experience of Collection Activity • Manual Connections Among Tools and Datasets • No Accessible Tools Designed for Collection Activity or Implementing Related Compensating Controls • Limited Affordances for Structured Archiving and Annotation • Context Switching Between Collection Tools and the Browsing Environment • Inability to Detect Exact and Near Duplicates
Information Integrations and Externalization	<ul style="list-style-type: none"> • Lack of Accessible Connectivity Affordances Among Teams and Platforms • Lack of Common Standards for Data Sharing • No Common Citation Method • Limited Affordances for Structured Archiving • Poor User Experience of Collection Activity • No Accessible Tools Designed for Collection Activity or Implementing Related Compensating Controls • Bias in Analysis
Making Analysis Useful	<ul style="list-style-type: none"> • Collection and Analysis Activity Not Fast Enough to Provide Situational Awareness in Real-time • Insufficient Standardization or Provenance Data to Allow for Reusability of Datasets

Table 2. Key Challenges in Methodological Collection

Automated Collection and Analysis	
Stage	Key Challenges
Data Engineering	<ul style="list-style-type: none"> • Lack of Accessible Connectivity Affordances Between Teams and Platforms
Data Analysis	<ul style="list-style-type: none"> • Insufficient Human-Annotated Data to Extract the Significance from the Relationships Between Text and Images • Lack of Common Standards and Ontology to Leverage in Connecting Image Memes to Functional Categories or Topics • Limited Human-Annotated Data Connecting Semantics and Semiotics (which could help with the automated extraction of latent topics within memes).

Table 3. Key Challenges in Automated Collection and Analysis

Requirements and Recommendations

Below we provide requirements for systems that might alleviate many of the key challenges for emergent teams tasked with analysis and annotation of image memes, and offer example use-cases if these requirements were made available.

Information Where it Matters. Analysts need access to information where it matters. Being able to access details on-site about existing analyses, collected artifacts, and to simply see whether or not a relevant object (e.g. an entity reference, an image meme, a thread, or a web page) has already been the subject of collection activity would immediately and unambiguously reduce most redundancies in collections activities. This could be achieved through custom browsers or, to avoid impacts from requiring platform adoption, through web and document annotation affordances. Tools that place collected information and analysis alongside the content itself would allow analysts to see their own shared lens on the internet without requiring content providers to adopt common standards.

Example Use-Cases

- Enriching images that have already been collected with summary information and links to extant analysis and related artifacts.
- Marking discussion threads and webpages with summary information about when they were last visited and what had been collected from them.

Dynamic Web Annotations. The ability to annotate and enrich content with links to and presentation of existing information would provide numerous benefits to analysts, including preventing redundant analysis and duplication during collection. However, the fact that some sources of artifacts are impactful because they are expected to change often (e.g., discussion threads) creates numerous challenges. The ability to annotate, or attach, 'functions' or 'automations' (i.e., triggers to run scripts) to web pages, which dynamically update their data and contents as opposed to presenting static content (e.g., text), could alleviate many of these challenges and add new analysis capabilities.

Example Use-Cases

- Updating analysts when content at a given URL has changed substantially or when content with certain characteristics have been detected.
- Tracking changes to sentiment or rate of engagement, indicating the presence of recent, potentially valuable artifacts.
- Performing image-similarity searches to “track” already collected images as they spread across the internet.

Proximal Collection and Tagging Affordances. The constant context-switching required for use of most tools offering collection affordances decreases productivity, information quality, and user experience and engagement generally. Providing collection affordances which are proximal to the source of artifacts would greatly enhance efficiency and user experience, thus improving information quality, rate of collection and productivity, and general engagement. For example, Paperpile, a reference management platform for academics, has used HTML injection and HTML template standards in order to insert artifact collection affordances on content of both static pages and search results in order to improve the productivity and efficiency of researchers (See Figure 8). Similar approaches using community-related features and more general and customizable templates and object standards could vastly improve digital artifact collection processes outside the context of academia.

Example Use-Cases

- Injection of collection affordances on web pages without requiring the permission of the web page’s owners or their adoption of common standards. This would enable users to quickly add artifacts for processing.
- Providing a computational basis for instituting compensating controls on collections. If the collection affordance is proximal to the source, a great deal of metadata about the artifact can be collected automatically, greatly reducing the amount of time taken per artifact while greatly increasing the information quality.

- Providing users and communities with the opportunity to share in common templates for computational detection and collection of different kinds of artifacts and their metadata on different websites (e.g., articles, posted comments, images).
- Offering tools that allow teams to set local scope and standards for collection and processing. As discussed, a multi-community process for annotation of semiotic content in images could lend a greater degree of objectivity to the analysis of rhetorical content. Further, the ability to set clear standards for these annotations (i.e. what and how annotation will be executed) could increase the longevity and applicability of the resulting datasets, and help communities choose the appropriate scope and level of detail for collection activity. For example, while analysts are unlikely to disagree about the semantic content within the images or text, finding consensus on rhetorical claims and the meaning of image memes may be impossible in some cases. Instead, comprehending the latent representations (i.e. semiotic content) in image memes may provide a useful common ground where human annotation can offer insight into the sensemaking that precedes the determination of rhetorical claims. Answering the question “What are the hidden representations, if any, that this meme signifies?” facilitates multiple answers. An analyst that didn’t have the appropriate background to uncover latent meaning could answer, “None.” Instead of forcing the analyst to deduce a single claim, semiotic-focused collection and analysis affords a softer approach more amenable to multi-user and multi-community analysis. In addition, an annotated dataset linking semantic and semiotic content would be re-usable by future analysts, and could be leveraged as training data to automate the process of sensemaking that underlies more complex forms of analysis (e.g. analysis of rhetorical claims).

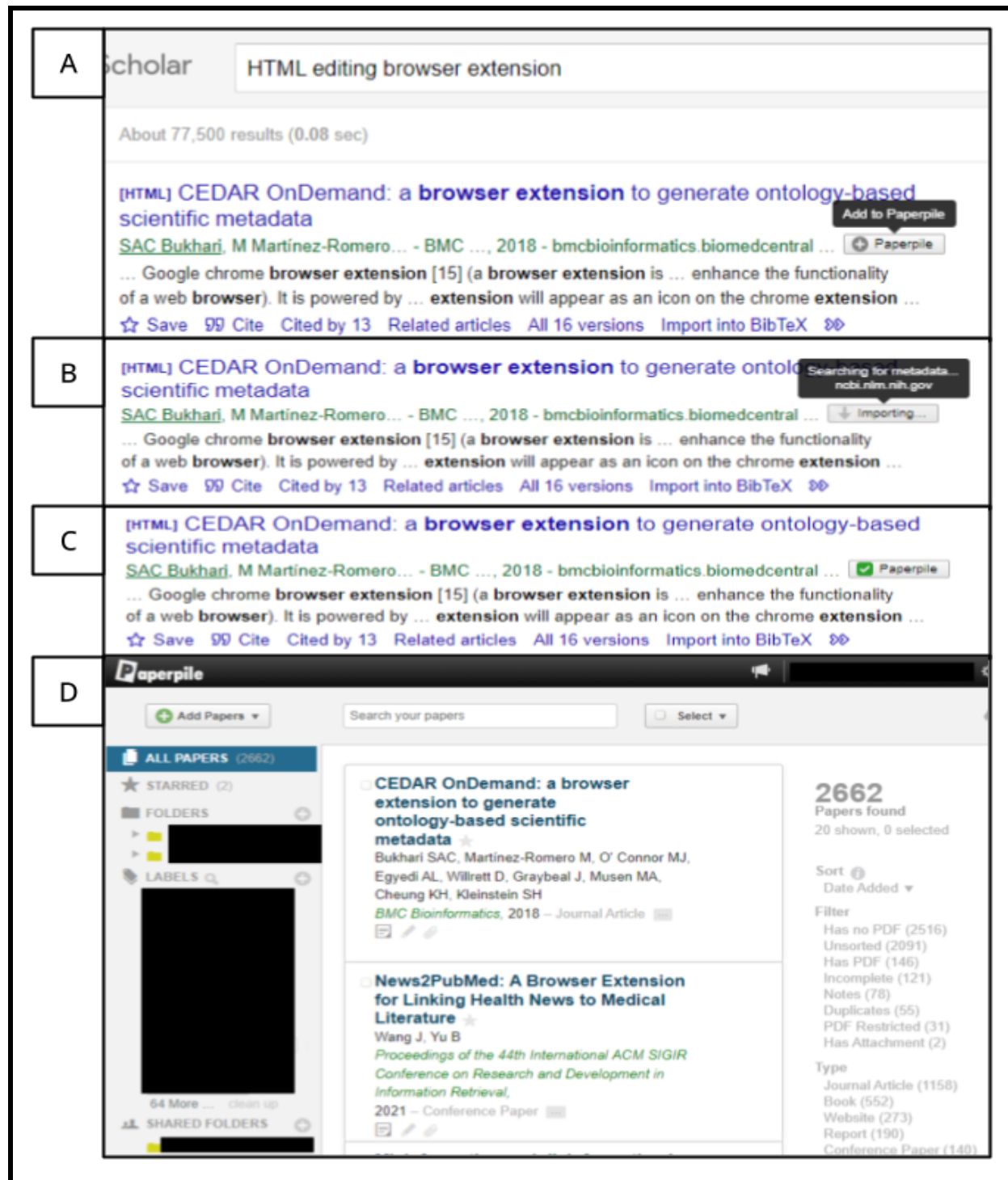


Figure 8. A 4-part graphic representing how Paperpile is used for digital artifact collection. (a) A detected artifact which has not yet been collected, (b) an artifact's attached collection affordance being used to search for related metadata, (c) how an artifact indicates that it has already been collected, and (d) how an artifact is represented in aggregate with other collected artifacts, with redactions of personal information.

Semantic Multimodal Search. Semantic multimodal search may be among the most needed and difficult-to-fulfill requests for analyst capabilities, as it has constituted a challenge for as long as humans have been actively attempting to refine methods for search, sort, and summarization of information across myriad contexts, from intelligence practice to library archiving [49–51]. While AI methods are presently the most popular approach to semantic search and collation, human annotation and analysis is the oldest, most auditable, and arguably the most reliable method available, despite its drawbacks [15,49,50,52]. The most notable of these drawbacks may be speed and scalability. These drawbacks can be addressed with crowdsourcing solutions, which adds new difficulties, such as the potential for disagreement regarding both the standards for and the resulting annotations.

However, given that the intent of artifact annotation in this case is to understand underlying claims, referenced entities, and cultural references, disagreement in well-structured and standardized annotation instead becomes valuable data for analysis [15,53]. Further, artifact annotation allows teams which externalize their collection and annotation activities to transcend local narrative bias and inherently limited cultural knowledge. Human annotation, at scale, facilitated by web annotation in combination with image-similarity algorithms, AI, and traditional ontological approaches, could yield the necessary semantic multi-modal search for aggregate analysis of highly subjective content, such as image memes [15]. These approaches could also provide training data to further externalize annotation to automated systems, enable connectivity between content and concepts, and offer the basis for identifying common hidden states, themes, claims, and references running through disparate content [15].

Example Use-Cases

- The PageRank algorithm is used to discover “which nodes [in a network] are important” whereas Reverse PageRank is “often used to determine why a particular node is important” [54]. While PageRank, and its cousin Reverse PageRank, are known for their use in internet search, the underlying mathematics are entirely general, and have been used in areas such as bioinformatics, neuroscience, literature and bibliometrics, and even sports [54]. With structured annotation, time-series metadata, and shared catalogs of image memes, there are a number of variations of search that become possible, from searching for which memes and themes or relevant URLs are or were important or trending, to

collating memes which are relevant given attribute-based search queries. Further, these forms of search may provide actionable insights for those performing or informing interventions, as they could point to image memes with highly specific attributes which can act as “stepping stones” or defenses for changing or maintaining beliefs, respectively, given audience characteristics and interests [18].

- With an annotated catalog of image memes and annotated automations for detecting image memes, it may be possible to not only search for specific memes or memes with specific attributes, but to search for where a meme has appeared and for its potential succeeding iterations. Similar to tagging and tracking methods in ecology, image memes could be tracked in real-time or through time-series projections as they move across the internet [15]. This kind of tracking, when paired with annotated automations for sentiment analysis over time, allows for search by sentiment impacts and trajectory potentials - offering the basis for dashboards, early warning systems, impact projections, and other predictive analytics and situational awareness systems [15].
- While search is generally associated with returned results from a specific query, there are numerous other forms of exploratory search, such as exploring connections in networks, interactive visualizations, and situational awareness tools [55]. Well annotated catalogs of image memes could allow for various exploration-facilitating visualizations, such as rhetorical and argument maps [56], process maps of meme lifecycles and transitions [32], and interactive network graphs [55].
- In addition, there could be forms of exploratory search as would be found in bioinformatics, such as network and graph exploration via functional annotation within the genome [57,58], allowing for analogous “memoinformatics” driven search within the memome. As functional significance has been imparted onto the human genome, our understanding of organismal biochemistry and physiology has progressed in turn. A detailed, hierarchical annotation of the memome that includes concepts, entities, semantic categories, semiotics, rhetoric, and the underlying links

between these types of content, could vastly increase our understanding of multimodal human communication, sensemaking, and cognition.

Separate Platforms, Shared Data. The limitation of current tools and the “one platform to rule them all” [59–61], or the “one app to replace them all” paradigm [62], has created and exacerbated challenges for teams attempting to effectively and efficiently collect, analyze, and implement common standards and controls for their data. As discussed, where individuals or their organizations come to the team with tool preferences, storage protocols and nomenclature, and rules about what tools can be used, teams are not only disjointed by default, but can disintegrate before they even have a chance to begin work. In addition, the team needs to be able to externalize some aspects of collection and integrate data with other teams that allow opportunities for selective disclosure, and create separations of concern within the team based on role and information needs. Even if there was a tool available which offered all of the affordances and capabilities the team could possibly need, it may still be more efficient, inclusive, and practical to “[meet] people where they are” [63,64].

Many companies are beginning to adopt a more collaborative approach, attempting to create new value through open standards and specifications. This open approach allows for digital asset and signal exchange with third-parties, and contributes API (application programming interface) connections and affordances to the “API economy” [65,66]. The API economy is composed of integration platform as a service (iPaas) [67,68], general automation platform (GAP) [69], cloud-based integration [70], and digital ecosystem [63] approaches. Companies such as Zapier [71], IFTTT [72], Make (formerly Integromat) [73], DOMO [74], MuleSoft [75], and Workato [70] provide the ability to create automations using “trigger-action” and “if-this-then-that” frameworks [71,72] and data pipeline integration capabilities that connect and incentivize the creation and use of APIs. These capabilities reduce the time-to-impact and the development and personnel costs of linking and maintaining data across multiple organizations, applications, and services [67,68]. However, not all platforms allow for these integrations and there can be a significant amount of work involved in enabling their use.

Incentivizing API economy participation through the use of common standards and market mechanisms for exchange of data with third parties might increase venture capital attention on companies using more open approaches with their data, thereby increasing the number of interoperable platforms. It can also offer alternative revenue streams to platforms which are currently disincentivized from sharing their data due to their reliance

on dwell time related revenues (i.e., advertising revenue). For example, while the meme collection site “Know Your Meme” is branded as a meme research and collection platform [76], it is also owned by a media holding company that collects advertising revenue from its underlying brands [77]. If Know Your Meme were provided with low-cost mechanisms to bring its collections to the API economy, the potential to offset ad revenue losses and create new business value might incentivize making data easily available to third-parties for other meme search, research, and curation functions. A more robust and accessible API economy could have large impacts on interorganizational work.

Example Use-Cases

- With accessible, low-code API integrations paired with methods for exchanging information about data standards and controls in use, the same mechanisms which help teams share calendar information between project management tools could be used to share data collections between teams in real-time.
- Role-based access controls and privileges can be difficult to manage and keep track of [55]. If teams have the ability to create ad hoc real-time connections between platforms, then, by proxy, they can implement highly complex role-based access and affordances simply by restricting membership on certain tools. This could allow for complex intelligence pipelines in which aspects of collection and expert analysis could be separated within teams, externalized to other teams with varying incentive sets (e.g., crowdsourced collection), or done in real-time collaboration with other teams and organizations.
- Some teams may have information they cannot or do not want to share, and, as discussed, some teams may have information they cannot receive without running afoul of internal ethical or other controls. API integration capabilities paired with clear opportunities for bidirectional selective disclosure could allow teams that would otherwise be unable to share information to communicate and collaborate. Further, allowing teams to set “terms of use” and related information on their offered or requested data would allow for a new level of transparency for users in how their shared information is used and governed [33].

Conclusion

As the world's increasing complexity drives conflict into increasingly abstract spaces [78], emergent teams involved in digital discourse analysis have a vital role to play in helping organizations maintain situational awareness and synthesize disparate perspectives generally. Here we advanced previous work on rhetorical analysis of image memes by presenting several archetypes of emergent teams involved in analysis, describing their inherent challenges, and suggesting recommendations for future systems design.

In the realm of image memes, which allow for unparalleled strategic ambiguity and plausible deniability, emergent teams may be the only viable approach to sensemaking in the digital rhetorical ecosystem - as no single organizational configuration can capture all of the symbols and cultural knowledge necessary to understand or estimate the significance of the content present. As discussed, the state of the art of image meme collection by emergent teams is not commensurate with either stakeholders' or the team's needs, despite direly needed affordances being well within technological reach. In short, there is a chasm between "how it is done today" and "how it could be done" that is not proportionate to the gap between "what is available" and "what is possible" (see Figure 9).

Digital ecosystem and API economy approaches seem to be a viable route to addressing many of the challenges discussed, and for enabling and contributing to the web and document annotation approaches which address the remaining challenges. API economy approaches have gained traction in recent years, and are now being applied across various areas of the market including agriculture [67,73], engineering [70], research [72] and marketing [69]. However for API economy approaches, lack of data standardization and integration capabilities remain a problem. This problem is not specific to challenges faced by emergent teams, and addressing it could be beneficial to a variety of sectors. Polling has suggested that the average enterprise uses more than 1,200 applications [79], and that an "average knowledge worker" is using up to 28 different applications [80] and is toggling between applications up to 10 times per hour [81]. According to Deloitte's 2021 Chief Procurement Officer Survey, among the top two barriers to effective technology implementation are data quality and poor integration capabilities across applications [82].

In addition to many other domains being able to share in the benefits of developments that would resolve challenges for emergent teams conducting image meme analysis, other domains can benefit from the resulting analysis. Resolving these challenges using the approaches discussed in this white paper could result in new claims-based methods to identify counterpublics and communities that have no formal affiliations, the capacity to

identify hidden states and themes running through public discourse, and to provide early warning systems indicating where streams of memes might constitute the precursor for groups to converge on (potentially violent) action.

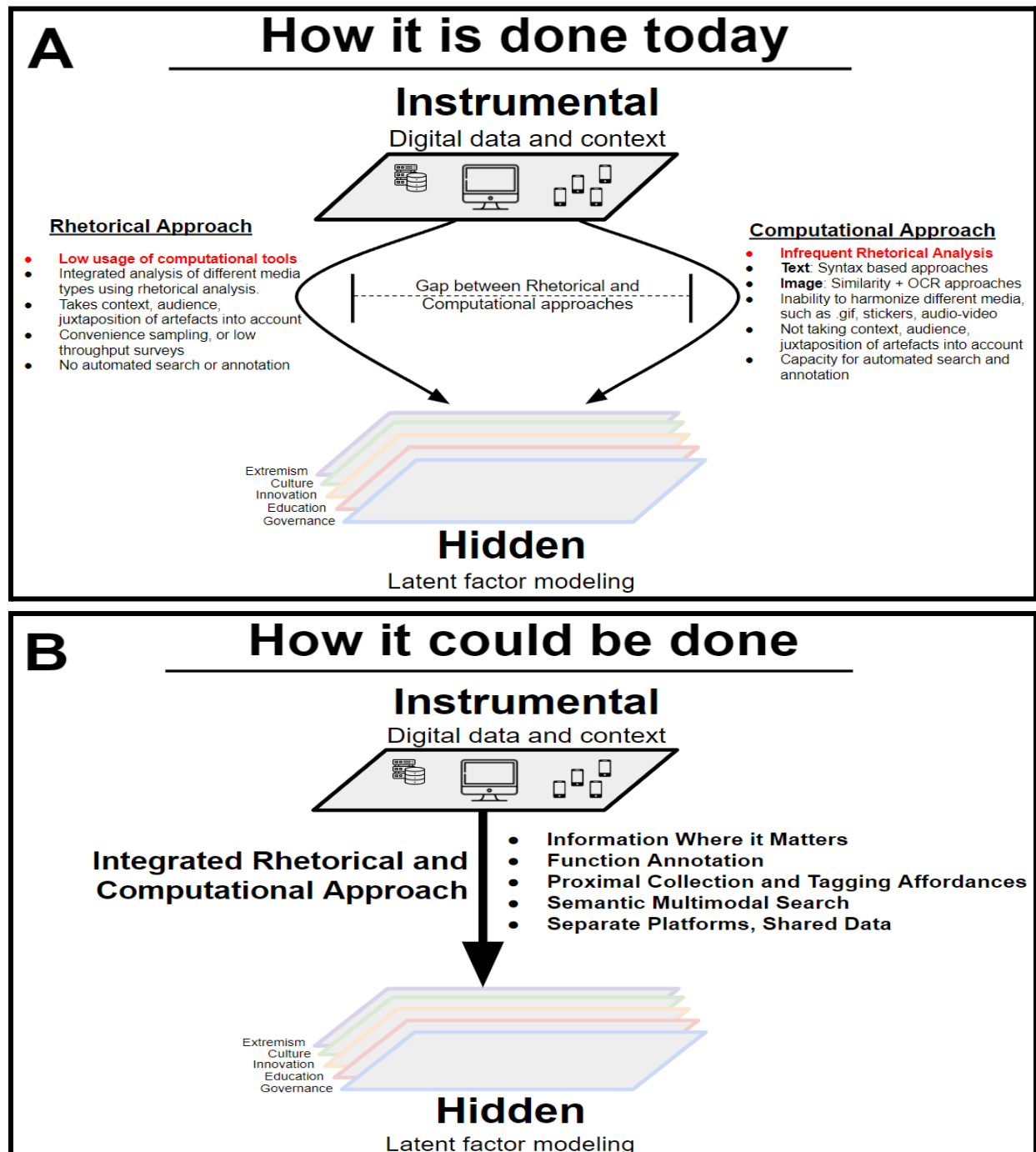


Figure 9. Graphical overview for computational and rhetorical analysis pipelines. A) How it is done today, and B) How it could be done.

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Works Cited

1. Roose K. A QAnon “Digital Soldier” Marches On, Undeterred by Theory’s Unraveling. The New York Times. 17 Jan 2021. Available: <https://www.nytimes.com/2021/01/17/technology/qanon-meme-queen.html>. Accessed 14 Jul 2022.
2. Castaño Díaz. Defining and characterizing the concept of Internet Meme. CES Psicol. 2013. Available: http://www.scielo.org.co/scielo.php?pid=S2011-30802013000200007&script=sci_arttext&tlng=en
3. Molina. What makes an internet meme a meme? Six essential characteristics. Handbook of visual communication. 2020. doi:10.4324/9780429491115-35/makes-internet-meme-meme-six-essential-characteristics-maria-molina
4. Dawkins R. The Selfish Gene. Oxford University Press; 2016.
5. Blackmore S. The Meme Machine. OUP Oxford; 2000.
6. Dennett DC. Darwin’s Dangerous Idea: Evolution and the Meanings of Life. Simon and Schuster; 1996.
7. Heylighen F. Selection criteria for the evolution of knowledge. Proc 13th Int Congress on Cybernetics. Association Internat. de Cybernétique; 1993. pp. 524–528.
8. Moreno-Almeida C. Memes as snapshots of participation: The role of digital amateur activists in authoritarian regimes. New Media & Society. 2021;23: 1545–1566.
9. de Saint Laurent C, Glăveanu VP, Literat I. Internet Memes as Partial Stories: Identifying Political Narratives in Coronavirus Memes. Social Media + Society. 2021;7: 2056305121988932.
10. Nieubuurdt JT. Internet Memes: Leaflet Propaganda of the Digital Age. Frontiers in Communication. 2021;5. doi:10.3389/fcomm.2020.547065
11. Mascarenhas M. Memes as Quasi-Argument. Local Theories of Argument. 2021. pp. 385–390. doi:10.4324/9781003149026-65
12. Observatory, DiResta, Cryst, Masterson, Small, Miller, et al. Memes, Magnets and Microchips: Narrative dynamics around COVID-19 vaccines. Virality Project. 2022. Available: <https://cyber.fsi.stanford.edu/io/publication/memes-magnets-and-microchips-narrative-dynamics-around-covid-19-vaccines>

13. Toulmin SE. *The Uses of Argument*. Cambridge University Press; 1958.
14. Ling C, AbuHilal I, Blackburn J, De Cristofaro E, Zannettou S, Stringhini G. Dissecting the Meme Magic: Understanding Indicators of Virality in Image Memes. *Proc ACM Hum-Comput Interact*. 2021;5: 1–24.
15. Mascarenhas M, Cordes RJ, Friedman DA. *Digital Rhetorical Ecosystem Analysis: Sensemaking of Digital Memetic Discourse*. Zenodo. 2021. doi:10.5281/zenodo.5573947
16. Chagas V, Freire F, Rios D, Magalhães D. Political memes and the politics of memes: A methodological proposal for content analysis of online political memes. *First Monday*. 2019. Available: <https://firstmonday.org/ojs/index.php/fm/article/view/7264/7731>
17. Zakem V, McBride MK, Hammerberg K. Exploring the utility of memes for US government influence campaigns. Center for Naval Analyses Arlington United States; 2018. Available: <https://apps.dtic.mil/sti/citations/AD1052398>
18. Cordes RJ, David S, Maan A, Ruiz A, Sapp E, Scannell P, et al. *The Narrative Campaign Field Guide - First Edition*. 1st ed. Cordes RJ, editor. Narrative Strategies Ink; 2021.
19. Cordes RJ. *The Next Generation of Security: Prioritizing Information Warfare Defense*. 7 Aug 2021 [cited 12 Aug 2021]. Available: <https://www.hstoday.us/subject-matter-areas/intelligence/the-next-generation-of-security-prioritizing-information-warfare-defense/>
20. Cordes RJ. Games with serious consequences: Extremist movements and kayfabe - Atlantic Council. In: atlanticcouncil.org [Internet]. 19 May 2021 [cited 3 Jun 2021]. Available: <https://www.atlanticcouncil.org/blogs/geotech-cues/games-with-serious-consequences-extremist-movements-and-kayfabe-2/>
21. Friedman DA, Cordes RJ. *Infinite Games for Infinite Teams. The Great Preset: Remote Teams and Operational Art*. COGSEC; 2020.
22. Taecharungroj V, Nueangjamnong P. Humour 2.0: Styles and Types of Humour and Virality of Memes on Facebook. *Journal of Creative Communications*. 2015;10: 288–302.
23. Guenther L, Ruhrmann G, Bischoff J, Penzel T, Weber A. Strategic Framing and Social Media Engagement: Analyzing Memes Posted by the German Identitarian Movement on Facebook. *Social Media + Society*. 2020;6: 2056305119898777.
24. Tindale CW. Replicating Reasons: Arguments, Memes, and the Cognitive Environment. *Philosophy & Rhetoric*. 2017;50: 566–588.
25. Ceccarelli L. Polysemy: Multiple meanings in rhetorical criticism. *Q J Speech*. 1998;84:

395–415.

26. Wikipedia contributors. Condensing Wonka. In: Wikipedia, The Free Encyclopedia [Internet]. 1 Jun 2021. Available: https://en.wikipedia.org/w/index.php?title=Condensing_Wonka&oldid=1026354342
27. Petty RE, Cacioppo JT. The Elaboration Likelihood Model of Persuasion. In: Berkowitz L, editor. *Advances in Experimental Social Psychology*. Academic Press; 1986. pp. 123–205.
28. Karlova N. Misinformation and disinformation in online games: an exploratory investigation of possible cues. digital.lib.washington.edu. 2018. Available: <http://digital.lib.washington.edu/researchworks/handle/1773/42416>
29. Hemsley, Snyder. Dimensions of visual misinformation in the emerging media landscape. Misinformation and mass audiences. 2018. Available: https://books.google.com/books?hl=en&lr=&id=jUw7DwAAQBAJ&oi=fnd&pg=PA91&dq=misinformation+artifacts&ots=Cv4UnjEdKZ&sig=DtirCALUY0-oCZ_ROpq8ZYBqQc
30. Cordes RJ, Friedman DA. Emergent Teams for Complex Threats. *The Great Preset: Remote Teams and Operational Art*. COGSEC; 2020. pp. 1–15.
31. Hürsch WL, Lopes CV. Separation of Concerns. 1995 [cited 24 Aug 2020]. doi:10.1.1.29.5223
32. Cordes RJ, Friedman DA, Maron M. Reimagining Maps. {National GeoSpatial Intelligence Agency Polyplexus Incubator}; 2020 Oct. doi:10.5281/zenodo.4170026
33. Karachiwalla R, Pinkow F. Understanding crowdsourcing projects: A review on the key design elements of a crowdsourcing initiative. *Creat Innov Manag*. 2021;30: 563–584.
34. Friedman D, Applegate-Swanson S, Choudhury A, Cordes RJ, El Damaty S, Guénin-Carlut A, et al. An Active Inference Ontology for Decentralized Science: from Situated Sensemaking to the Epistemic Commons. 2022. doi:10.5281/zenodo.6320575
35. Jamal U. Facebook is reversing its ban on posts praising Ukraine’s far-right Azov Battalion, report says. *Business Insider*. 25 Feb 2022. Available: <https://www.businessinsider.com/facebook-reverses-ban-praise-ukraine-far-right-force-s-2022-2>. Accessed 19 May 2022.
36. Cordes RJ, Friedman DA. The Facilitator’s Catechism. In: Friedman DA, Cordes RJ, editors. *The Great Preset: Remote Teams and Operational Art*. COGSEC; 2020.
37. StoneToss. Fast Friends Image Meme. In: stonetoss.com [Internet]. 24 Mar 2022 [cited 18 May 2022]. Available: <https://stonetoss.com/comic/fast-friends/>

38. Ukraine and Putin RN. In: 9GAG [Internet]. 1 Mar 2022 [cited 23 May 2022]. Available: <https://9gag.com/gag/a21vjMe>
39. van Brugen I. Russia Arrests Multiple People for Holding Up Blank Signs. In: Newsweek [Internet]. 14 Mar 2022 [cited 23 May 2022]. Available: <https://www.newsweek.com/russia-ukraine-war-invasion-protests-police-arrest-activist-s-holding-blank-signs-paper-1687603>
40. Heuer RJ. Psychology of Intelligence Analysis. Center for the Study of Intelligence; 1999.
41. Jervis R. Perception and Misperception in International Politics. Princeton University Press; 2017.
42. Potamias RA, Siolas G, Stafylopatis A-G. A transformer-based approach to irony and sarcasm detection. *Neural Comput Appl*. 2020;32: 17309–17320.
43. Koutlis C, Schinas M, Papadopoulos S. MemeTector: Enforcing deep focus for meme detection. *arXiv [cs.CV]*. 2022. Available: <http://arxiv.org/abs/2205.13268>
44. Sinha A, Patekar P, Mamidi R. Unsupervised Approach for Monitoring Satire on Social Media. *Proceedings of the 11th Forum for Information Retrieval Evaluation*. New York, NY, USA: Association for Computing Machinery; 2019. pp. 36–41.
45. Chen E. 30% of Google's Emotions Dataset is Mislabeled. 14 Jul 2022 [cited 14 Jul 2022]. Available: <https://www.surgehq.ai//blog/30-percent-of-googles-reddit-emotions-dataset-is-mislabeled>
46. Wei P, He F, Zou Y. Content semantic image analysis and storage method based on intelligent computing of machine learning annotation. *Neural Comput Appl*. 2020;32: 1813–1822.
47. Henning C, Ewerth R. Estimating the information gap between textual and visual representations. *International Journal of Multimedia Information Retrieval*. 2018;7: 43–56.
48. Otto C, Springstein M, Anand A, Ewerth R. Characterization and classification of semantic image-text relations. *International Journal of Multimedia Information Retrieval*. 2020;9: 31–45.
49. Blair AM. Too Much to Know. Yale University Press; 2010.
50. Mangold C. A survey and classification of semantic search approaches. *Int J Metadata Semant Ontol*. 2007;2: 23–34.
51. Waltz E. Knowledge Management in the Intelligence Enterprise. Artech House; 2003.

52. Kent S. Strategic Intelligence for American World Policy. Princeton University Press; 1949.
53. Tamari R, Friedman D, Fischer W, Hebert L, Shahaf D. From Users to (Sense)Makers: On the Pivotal Role of Stigmergic Social Annotation in the Quest for Collective Sensemaking. arXiv [cs.SI]. 2022. Available: <http://arxiv.org/abs/2205.06345>
54. Gleich DF. PageRank Beyond the Web. SIAM Rev. 2015;57: 321–363.
55. Cordes RJ, Applegate-Swanson S, Friedman DA, Knight VB, Mikhailova A. Narrative Information Management. In: Cordes RJ, Friedman DA, editors. Narrative Information Ecosystems: Conflict and Trust on the Endless Frontier. COGSEC; 2021. pp. 1–64.
56. Kashcha A. Map of Reddit. In: anvaka.github.io [Internet]. [cited 16 Jun 2022]. Available: <https://anvaka.github.io/map-of-reddit/?x=137263.0138067139&y=331978.27245969005&z=967321.673408511>
57. Search by Functional Annotation. In: genomehubs.org [Internet]. [cited 21 Jul 2022]. Available: <https://genomehubs.org/communities/tutorials/search-by-functional-annotation/>
58. Shannon P, Markiel A, Ozier O, Baliga NS, Wang JT, Ramage D, et al. Cytoscape: a software environment for integrated models of biomolecular interaction networks. Genome Res. 2003;13: 2498–2504.
59. Adobe. One Platform to Rule Them All: 5 reasons to choose a hybrid platform that combines B2B and B2C capabilities. 2019 Feb.
60. Solarwinds. “One Platform to Rule Them All”: How SolarWinds provided IT visibility across the VA’s enterprise. In: Federal News Network [Internet]. 30 Oct 2019 [cited 24 Jun 2022]. Available: <https://federalnewsnetwork.com/innovation-in-government-success-stories/2019/10/one-platform-to-rule-them-all-how-solarwinds-provided-it-visibility-across-the-vas-enterprise/>
61. Dunn J. One Platform To Rule Them All: How N2N Makes Life Easier for Smaller Institutions. In: illuminateapp.com [Internet]. 7 Jun 2019 [cited 24 Jun 2022]. Available: <https://illuminateapp.com/web/EnlightenEd/one-platform-to-rule-them-all-how-n2n-makes-life-easier-for-smaller-institutions/>
62. Reed J. One app to replace them all? In: diginomica [Internet]. 3 Feb 2021 [cited 24 Jun 2022]. Available: <https://diginomica.com/one-app-replace-them-all-clickups-ceo-future-productivity-and-how-clickup-addresses-proliferation>
63. Mattr. Mattr - Building an Open and Interoperable Ecosystem for Digital Trust. In:

- Mattr.global [Internet]. 2021 [cited 29 Jun 2022]. Available: <https://mattr.global/approach/>
64. Norman D. The Design of Everyday Things: Revised and Expanded Edition. Basic Books; 2013.
 65. Gamez-Diaz A, Fernandez P, Ruiz-Cortes A. An Analysis of RESTful APIs Offerings in the Industry. Service-Oriented Computing. Springer International Publishing; 2017. pp. 589–604.
 66. Soomro, Awan. Challenges and Future of Enterprise Application Integration. Int J Comput Appl. 2012. Available: <http://www.ijcaonline.org/archives/volume42/number7/5708-7762>
 67. Cestari RH, Ducos S, Exposito E. iPaaS in Agriculture 4.0: An Industrial Case. 2020 IEEE 29th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE). ieeexplore.ieee.org; 2020. pp. 48–53.
 68. Gartner. Definition of Integration Platform as a Service (iPaaS). In: Gartner Information Technology Glossary [Internet]. [cited 30 Jun 2022]. Available: <https://www.gartner.com/en/information-technology/glossary/information-platform-as-a-service-ipaas>
 69. Ortiz A, Waldron R, Taylor H. The Beginner's Guide to General Automation Platforms. 2019.
 70. Frantz RZ, Corchuelo R, Basto-Fernandes V, Rosa-Sequeira F, Roos-Frantz F, L. Arjona J. A cloud-based integration platform for enterprise application integration: A Model-Driven Engineering approach. Softw Pract Exp. 2020. doi:10.1002/spe.2916
 71. Rahmati A, Fernandes E, Jung J, Prakash A. IFTTT vs. Zapier: A Comparative Study of Trigger-Action Programming Frameworks. arXiv [cs.CR]. 2017. Available: <http://arxiv.org/abs/1709.02788>
 72. Ovadia S. Automate the Internet With “If This Then That” (IFTTT). Behav Soc Sci Librar. 2014;33: 208–211.
 73. Singh, Iqbal, Singh, Kumar. Smart garden with iot based plant monitoring system. IEEE Solid-State Circuits Soc Newsl. 2020. Available: https://www.researchgate.net/profile/Surya-Singh-2/publication/353878999_Smart_Garden_with_IoT_based_Plant_Monitoring_System/links/611632f00c2bfa282a3f72fb/Smart-Garden-with-IoT-based-Plant-Monitoring-System.pdf
 74. DOMO. DOMO Data Integration. In: Domo.com [Internet]. [cited 6 Jul 2022]. Available: https://www.domo.com/solution/data-integration?utm_source=google&utm_medium=paidsearch&campid=7015w000000vIPfAAI&gcreative=474206076414&gdevice=c&gnet

work=g&gkeyword=application%20interface&gplacement=&gmatchtype=p>arget=&gadposition=&s_kwcid=AL!5964!3!474206076414!p!!g!!application%20interface&gclid=Cj0KCQjw5ZSWBhCVARIsALERCvyz8XHgFUQc-ylxkHj8NvRiT3BoOkbAbdEp0L_-gX8k6GWClO5Jt3kaAghiEALw_wcB

75. MuleSoft. What is an API Economy. In: MuleSoft [Internet]. [cited 21 Jul 2022]. Available: <https://www.mulesoft.com/resources/api/what-is-an-api-economy>
76. KnowYourMeme. About Know Your Meme. In: Know Your Meme [Internet]. [cited 6 Jul 2022]. Available: <https://knowyourmeme.com/about>
77. LiterallyMedia. Literally – Home of Legendary Brands. In: Literally Media [Internet]. [cited 6 Jul 2022]. Available: <https://literally.media/>
78. David S, Cordes RJ, Friedman DA. Active Inference in Modeling Conflict. 2021. doi:10.5281/zenodo.5750935
79. Netskope Marketing. Netskope Cloud Report - August 2019. 1 Aug 2019 [cited 30 Jun 2022]. Available: <https://resources.netskope.com/cloud-security-infographics/netskope-cloud-report-august-2019-2>
80. Ismail K. How To Manage Digital Workplace Tool Overload. In: CMSWire.com [Internet]. 1 Nov 2017 [cited 30 Jun 2022]. Available: <https://www.cmswire.com/digital-workplace/how-to-manage-digital-workplace-tool-overload/>
81. Eide N, Bolden-Barrett V. App overload wastes 32 days of employee productivity each year. In: ciodive.com [Internet]. 7 Mar 2018 [cited 30 Jun 2022]. Available: <https://www.ciodive.com/news/app-overload-wastes-32-days-of-employee-productivity-each-year/518520/>
82. Kilpatrick J, Brown J, Flynn R, Addicoat A, Mitchell P. Deloitte Global 2021 Chief Procurement Officer Survey. In: Deloitte Insights [Internet]. Deloitte; 23 Apr 2021 [cited 30 Jun 2022]. Available: <https://www2.deloitte.com/global/en/insights/topics/operations/chief-procurement-officer-cpo-survey.html>