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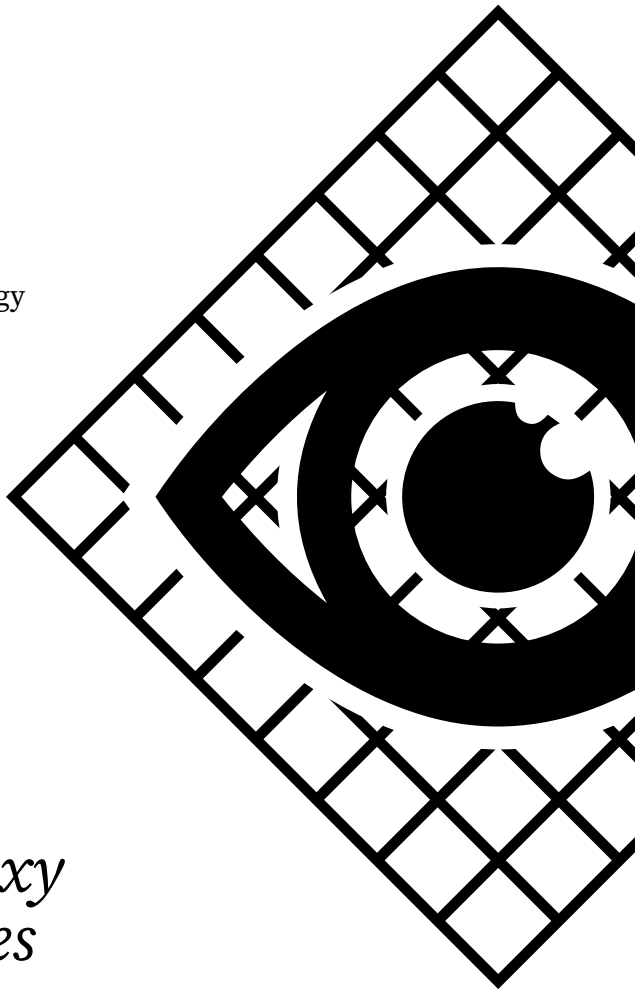

Surveillance Graphs

Vulgarity and Cloud Orthodoxy in Linked Data Infrastructures

Information is power, and that power has been largely enclosed by a handful of information conglomerates. The logic of the surveillance-driven information economy demands systems for handling mass quantities of heterogeneous data, increasingly in the form of knowledge graphs. An archaeology of knowledge graphs and their mutation from the liberatory aspirations of the semantic web gives us an underexplored lens to understand contemporary information systems. I explore how the ideology of cloud systems steers two projects from the NIH and NSF intended to build information infrastructures for the public good to inevitable corporate capture, facilitating the development of a new kind of multilayered public/private surveillance system in the process. I argue that understanding technologies like large language models as interfaces to knowledge graphs is critical to understand their role in a larger project of informational enclosure and concentration of power. I draw from multiple histories of liberatory information technologies to develop Vulgar Linked Data as an alternative to the Cloud Orthodoxy, resisting the colonial urge for universality in favor of vernacular expression in peer to peer systems.

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Contents

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Note: This piece is an extension of "Linked Data or Surveillance Capitalism" in **Decentralized Infrastructure for (Neuro)science** [1] and reproduces text from it in whole and in part.

1 Introduction

The world is Big Data, and The Cloud is its landlord. It is our responsibility to ferret it out of its primitive unknown, mine it, harvest it, dump it by the tanker-truckful into great Data Lakes overhung by computational Clouds to refine the Actionable Insights from its desiccated husk. The Cloud promises us an infinite, seamless expanse of Knowledge. If only we can harness the wily spray of our Organic Content, filtering our every action, affection, and affiliation through a thicket of algorithmically optimized platforms then The Cloud might teach us enough about ourselves to finally be happy. Information by its many names is the central quilting point for contemporary capitalism (eg. see [2]), and like prior assemblages of capital is thick with contradiction. It is historically contingent and inevitable, material and transcendent, a concrete set of technologies and techniques as well as a web of belief systems, power, and *dreams.* The Cloud now dreams of a great Knowledge Graph of Everything, to Dissolve the Silos that keep the Bigness of Data from teaching us all we could know. It tells us this is important for the fate of humanity.

The Knowledge Graph of Everything and all that it promises is a mirage, though. Its history is that of "primitive accumulation" of informational capital, the widening of informational asymmetries, and the logical conclusion of a model of digital serfdom where we are promised glimpses of unimaginable computational power through the pinhole lens of platforms for rent. With the enclosure of the web nearly total, and our ability to imagine it in any other form eclipsed, information conglomerates now position themselves as information "Infrastructures" rather than mere Platforms [3, 4] . The politics, property and power relationships of the contemporary web recede into the background of always-on elastic computation. Public resources are rallied to build seemingly public data infrastructures to feed far-flung facets of public life to systems built for decidedly private profit. Aside from the pathological nature of the Knowledge Graph of Everything as a colonial vision of all data being put in its one True order, it *is impossible* and *won't work.* Instead, by uncritically adopting the logic of The Cloud, governments and academics will be led along by the nose just long enough to build critical mass for an interlocking set of platforms that ratchet us ever further into the captivity of surveillance.

Approaching the information-surveillance-platform archipelago through knowledge graphs gives us an underexplored lens with which to understand the politics of contemporary data infrastructures. Their history, the development from the liberatory ambitions of the Semantic Web and Linked Data into the panoptical data systems of the surveillance economy, is rich with 'paths not taken' from which we can reimagine a future. Two contemporary projects from the National Institutes of Health (NIH) and National Science Foundation (NSF) illustrate the ways our ambitions for public data infrastructures are steered by the constraints of the cloud and the imminent capacity for harm that poses. Rather than some obscure squabble between academics, public knowledge graph projects intersect squarely with the ideological foundation of The Cloud along with the parallel strains of "AI" to show how Large Language Models (LLMs) are the tools for the next great extension of surveillance capitalism and re-entrenchment of informational dominance.

The past, present, and future of knowledge graphs give us the pieces to articulate a properly *human* data infrastructure as **vulgar linked data**. Predicated on relationality, heterogeneity, distribution of power, and vernacular expression, vulgar linked data infrastructures attempt to empower *people* to *socially organize* information in a truly decentralized sociotechnological commons, rather than empowering *systems* to *rent* knowledge organization for *profit.*

2 Knowledge Graphs: A Backbone in the Surveillance Economy

Knowledge graphs as a technology are relatively straightforward to define [5, 6, 7, 8] (though see [9]): **directed, labeled graphs** consisting of *nodes* corresponding to entities like a person, dataset, location, etc. and *edges* that describe their relationship[1]. Knowledge graphs typically make use of some controlled **ontology** that provides a specific set of terms for nodes and edges and how they are to be used, and "types" that give a given entity an expected set of *properties* represented by edges. This makes for an extremely general data structure, where heterogeneous data can form a continuous graph in a way that is both structured and can accommodate ad-hoc modification not anticipated by a schema. For example, in Wikidata, Peter Kropotkin (Q5752) is an instance of the "human" type, which has properties like `sex or gender` (male) and `place of birth` (Moscow), but also has additional properties not in the `human` type like `signature`. Each of the "edges" like `place of birth` link to other nodes like `Moscow`, which in turn have their own sets of links, and so on.

[1] Equivalently, one could emphasize that they are graphs composed of **triplet** links (or just **triplets**) that describe some subject, predicate, and object.

Knowledge graphs are in themselves a fairly ordinary class of data structures and technologies, but their history is the story of the enclosure of the wild and open web into a series of surveillance-backed platforms.

2.1 Semantic Web: Priesthoods

The term "Knowledge Graph" evolved out of the Semantic Web project [6] , and so we rewind to the start point of our history at the end of the 90's. It is difficult to reconstruct how radical the notion of a collection of documents organized by arbitrary links between them was at dawn of the internet. At the time, the infrastructures of linking documents looked more like ISBNs, carefully regulated by expert, centralized authorities[2]. Being able to *just link to anything* was *terrifying* and *new* (eg. [10, 11]).

[2] For another example re: the political nature of the DOI system in the face of the arbitrary linking of the internet, see section 3.1 below or section 3.1.2 "Integration, not Invention" in [1]

The initial design of the web imagined it as a self-organizing process, where people would maintain their own websites and organize a collection of links to other websites[3]. It became clear relatively quickly that the anarchy of a socially self-organizing internet wasn't going to work as planned, where without a formal system of organization "people were frightened of getting lost in it. You could follow links forever." [12]

[3] For example, see the Tour Bus system in early wikis, where each wiki would agree to link to the next wiki in the "bus line," so someone that landed at the Meatball Wiki Bus Stop and was interested in seeing "eclectic" wikis would continue on through (now defunct) WikiTravel and ToothyWiki.

Like the radical nature of linking on the web, it's difficult to remember that the web as surveillance apparatus thinly veiled as the five or so remaining platform-websites was not inevitable. The pre-dotcom bust internet of the 90's and early 2000's was far from the commercialized wasteland we know today. Ed Horowitz, CEO of Viacom explained in 1996: "The Internet has yet to fulfill its promise of commercial success. Why? Because there is no business model" [13] . Google's AdWords being a defining moment in the development of surveillance capitalism is a story already told [14] : taking advantage of the need for search generated by the disorganization of the web, AdWords turned personal search data into a profit vector by selling targeted space in the results.

The significance of the relationship between search, the semantic web, and what became knowledge graphs is less widely appreciated. The semantic web was initially an alternative to monolithic search engine platforms - or, more generally, to platforms in general [15] . It imagined the use of triplet links and shared ontologies at a protocol level as a way of organizing the information on the web into a richly explorable space: rather than needing to rely on a search bar, one could traverse a structured graph of information [16, 17] to find what one needed without mediation by a third party.

The Semantic Web project was an attempt to supplement the arbitrary power to ex-

press human-readable information in linked documents with computer-readable information. It imagined a linked and overlapping set of schemas ranging from locally expressive vocabularies used among small groups of friends through globally shared, logically consistent ontologies. The semantic web was intended to evolve fluidly, like language, with cultures of meaning meshing and separating at multiple scales [18, 19, 20] :

> Locally defined languages are easy to create, needing local consensus about meaning: only a limited number of people have to share a mental pattern of relationships which define the meaning. However, global languages are so much more effective at communication, reaching the parts that local languages cannot. [...]
>
> So the idea is that in any one message, some of the terms will be from a global ontology, some from subdomains. The amount of data which can be reused by another agent will depend on how many communities they have in common, how many ontologies they share.
>
> In other words, one global ontology is not a solution to the problem, and a local subdomain is not a solution either. But if each agent has uses a mix of a few ontologies of different scale, that is forms a global solution to the problem. [18]

> The Semantic Web, in naming every concept simply by a URI, lets anyone express new concepts that they invent with minimal effort. Its unifying logical language will enable these concepts to be progressively linked into a universal Web. [19]

This free form goal of expression for expression's sake was always in tension with another part of the vision - serving as a backbone for AI "agents" that could compute emergent function from the semantic web. Succinctly: "Human language thrives when using the same term to mean somewhat different things, but automation does not." [19] This tension persists through the broader history of the web, and we will return to it soon.

2.2 Linked Data: Platforms

Much of the work of the semantic web project in the early 2000s focused on the "global" side of this tension at the expense of the "local" - creating ontologies and related technologies intended to serve as a foundation for expressing basic things in a common vocabulary [6] . This work had many successes, but began a schism between the priesthood of people concerned with making systems that were *correct* and those that were more concerned with making things that *worked* - or supported "local" expression (eg [21]). Aaron Swartz captured this frustration in his unfinished book:

> Instead of the "let's just build something that works" attitude that made the Web (and the Internet) such a roaring success, they brought the formalizing mindset of mathematicians and the institutional structures of academics and defense contractors. They formed committees to form working groups to write drafts of ontologies that carefully listed (in 100-page Word documents) all possible things in the universe and the various properties they could have, and they spent hours in Talmudic debates over whether a washing machine was a kitchen appliance or a household cleaning device. [22]

Lindsay Poirier describes this difference in "thought styles" as a rift between the "neats" focused on universalizing *a priori* ontologies and the "scruffies" focused on everyday use and letting the structure appear afterwards [23] . The latter characterizes the "second age" of the Semantic Web after 2006 - the reorganization around **Linked Data** [16, 6] . The era of Linked Data de-emphasized the idealistic and ideological goals of the early Semantic Web, driven more by an empirical approach of trying to realize these systems on the wilds of the web, creating some of the first

public “Linked Open Data” systems like DBPedia and Freebase.

This turn coincides with the emerging platformatization and enclosure of the web as “Web 2.0.” Throughout the early 2000s, the work of the Semantic Web project was largely invisible to the ordinary web user, and its vision of a self-organizing web was easily outcompeted by the now-ubiquitous use of search engines to index the web. Where in the early 2000s web architects were imagining the future of web continuing to take place on free and open *protocols,* the Linked Data/Web 2.0 era corralled us into a pattern of *platforms* which quickly ratcheted their way to dominance in a positive feedback loop of user experience design, network effects, and profit. On platforms, rather than a system that “belongs” to everyone, you are granted access to some specific set of operations through an interface so that you can be part of a social process of producing and curating information for the platform holder. Shifting focus from the idealistic vision of public, protocol-driven self-organization to platforms for declaring and consuming semantic web data resulted in a lot of functional tools, but also ripened the project for capture.

2.3 Knowledge Graphs: Panoptica

In 2010 Google acquired Metaweb and its publicly-edited Semantic Web database Freebase, and in 2012 repackaged it and the ideas of Linked Data as what it called a **Knowledge Graph** — the third era of the Semantic Web [24, 25] . Freebase only made up part of it, and the full extent of Google’s Knowledge Graph is unknown, but its most visible impact are the factboxes that present structured information about the subjects of searches - like biographical information in a search for a person, or the different widgets for contextual interaction like restaurant reservations[4] [26] . Knowledge Graphs still share the same underlying structure — triplet graphs with ontologies — even if they occupy a broader space of implementations and technologies. What differs is the context and intended use: the “worldview” of the knowledge graph.

[4] The imagination of the bored, middle class platform developer seems to be populated primarily by ordering food from restaurants and shopping.

Beyond the obvious product-level features it supports, Google’s acquisition of Freebase and the structure of its Knowledge Graph represent at least two deeper shifts in the trajectory of the Semantic Web and the broader internet: the privatization of technologies with initially liberatory aspirations, and an early template of the all too familiar sprawling, surveillance-driven information conglomerate.

The form of of the semantic web that emerged as “Knowledge Graphs” flipped the vision of a free and evolving internet on its head. The mutation from “Linked Open Data” [16] to “Knowledge Graphs” is a shift in meaning from a public and densely linked web of information from many sources to a proprietary information store used to power derivative platforms and services. The shift isn’t quite so simple as a “closure” of a formerly open resource — we’ll return to the complex role of openness in a moment. It is closer to an *en*closure, a *domestication* of the dream of the Semantic Web. A dream of a mutating, pluralistic space of communication, where we were able to own and change and create the information that structures our digital lives was reduced to a ring of platforms that give us precisely as much agency as is needed to keep us content in our captivity. Links that had all the expressive power of utterances, questions, hints, slander, and lies were reduced to mere facts. We were recast from our role as *people* creating a digital world to *consumers* of subscriptions and services. The artifacts that we create for and with and between each other as the substance of our lives online were yoked to the acquisitive gaze of the knowledge graph as *content* to be mined. We vulgar commoners, we data subjects, are not allowed to touch the graph — even if it is built from our disembodied bits.

The same technologies, with minor variation, that were intended to keep the internet free became emblematic of and coproductive with the surveillance/platform model that has enclosed it. Beyond Google, knowledge graphs are an elemental part of the information economy. Banks, militaries, governments, life science corporations, journalists, everyone is using knowledge graphs [27, 28] . Their ubiquity

is not an accident, one of many possible data systems that could have fit the bill, but reflects and reinforces basic patterns of the information economy and the corporations within it. Conveniently, semantic web technologies, designed to accommodate the infinitely heterogeneous, multiscale nature of free and unmediated social structuring of information are also quite useful for the indefinitely expanding dragnet of data collection that defines the operation of contemporary capitalism.

Data companies — most major companies[5] — need to store and maintain massive collections of heterogeneous data across their byzantine hierarchies of executives, managers, and workers. This gigantic haunted ball of data is not just a tool, but the *substance* of the company. A data company persists by exploiting the combinatorics of its data hoard, spinning off new platforms that in turn maintain and expand access to data by creating captive data subjects[6]. As it expands, a conglomerate will acquire many new sources and modalities of data and need to integrate them with its existing data.

Knowledge graphs are particularly well suited for this "data integration" problem. A full technical description is out of scope here, but briefly: traditional relational database systems can be very difficult to modify and refactor, and that difficulty increases the larger and more complex a database is[7]. One has to design the structure of the anticipated data in advance, and the abstract schematic structure of the data is embedded in how it is stored and accessed. It is particularly difficult to do unanticipated "long range" analyses where very different kinds of data are analyzed together.

In contrast, merging graphs is more straightforward[8] [5, 28, 29, 30, 31, 32, 33, 34] - the data is just triplets, so in an idealized case[9] it is possible to just concatenate them and remove duplicates (eg. for a short example, see [35, 36]). The graph can be operated on locally, with more global coordination provided by ontologies and schemas, which themselves have a graph structure [37] . Discrepancies between graphlike schema can be resolved by, you guessed it, making more graph to describe the links and transformations between them. Long-range operations between data are part of the basic structure of a graph - just traverse nodes and edges until you get to where you need to go - and the semantic structure of the graph provides additional constraints to that traversal. Again, a technical description is out of scope here, graphs are not magic, but they are well-suited to merging, modifying, and analyzing large quantities of heterogeneous data[10].

So if you are a data broker, and you just made a hostile acquisition of another data broker who has additional surveillance information to fill the profiles of the people in your existing dataset, you can just stitch those new properties on like a fifth arm on your nightmarish data Frankenstein.

What does this look like in practice? While in a bygone era Elsevier was merely a rentier holding publicly funded research hostage for profit, its parent company RELX is paradigmatic of the transformation of a more traditional information rentier into a sprawling, multimodal surveillance conglomerate (see [38]). RELX proudly describes itself as a gigantic haunted graph of data (Fig. 1):

> Technology at RELX involves creating actionable insights from big data – large volumes of data in different formats being ingested at high speeds. We take this high-quality data from thousands of sources in varying formats – both structured and unstructured. We then extract the data points from the content, link the data points and enrich them to make it analysable. Finally, we apply advanced statistics and algorithms, such as machine learning and natural language processing, to provide professional customers with the actionable insights they need to do their jobs.
>
> We are continually building new products and data and technology platforms, re-using approaches and technologies across the company to create platforms

[5]

> "If one takes a look at the top Fortune 500 companies, it is surprising how many of them are really in the information business. I don't just mean the technology and telecommunication companies like Apple or Google or Verizon or Cisco or the drug companies like Pfizer. One could also think of the big banks as a subset of the vectoralist class rather than as "finance capital." They too are in the information asymmetry business. And as we learned in the 2008 crash, even the car companies are in the information business—they made more money from car loans than cars. The military—industrial sector is also in the information business. The companies that appear to sell actual things, like Nike, are really in the brand business. Walmart and Amazon compete with different models of the information logistics business. Even the oil companies are in part at least in the information-about-the-geology-of-possible-oil-deposits business. Perhaps the vectoralist class is no longer emerging. Maybe it is the new dominant class." [2]

[6] Facebook describes its platform as being just a means of interacting with its underlying data graph in the jargon of corporate web design: "A useful tool for Facebook has been to think of the graph as the model and a Facebook page as the view—a projection of an entity or collection of entities that reside in the graph." [26]

[7] For a practical example, see a recent trio of blog posts from Etsy engineers that describe the process of scaling their database system.

[8]

> That is because knowledge graphs aim to solve the data incongruence problem, which is one of the biggest operational headaches for corporates, says Atkin. "Corporates suffer from technology fragmentation and as a result have a lot of data that doesn't align across the organization. Doing the hard work to fix this data incongruence reality is a pre-requisite for realizing business value," he says. [29]

[9] I am aware graph databases are not magic and this is an extraordinarily simplified example. The principle is the point, not all the subtle ways the implementations of graph databases are hard.

[10] Another way of looking at the capacity for heterogeneity in triplet graphs is by thinking of links as statements:

> One person may define a `vehicle` as having a `number of wheels` and a `weight` and a `length`, but not foresee a `color`. This will not stop another person making the assertion that a given car is `red`, using the color vocabulary from elsewhere. [12]

that are reliable, scalable and secure. **Even though we serve different segments with different content sets, the nature of the problems solved and the way we apply technology has commonalities across the company.** [39]

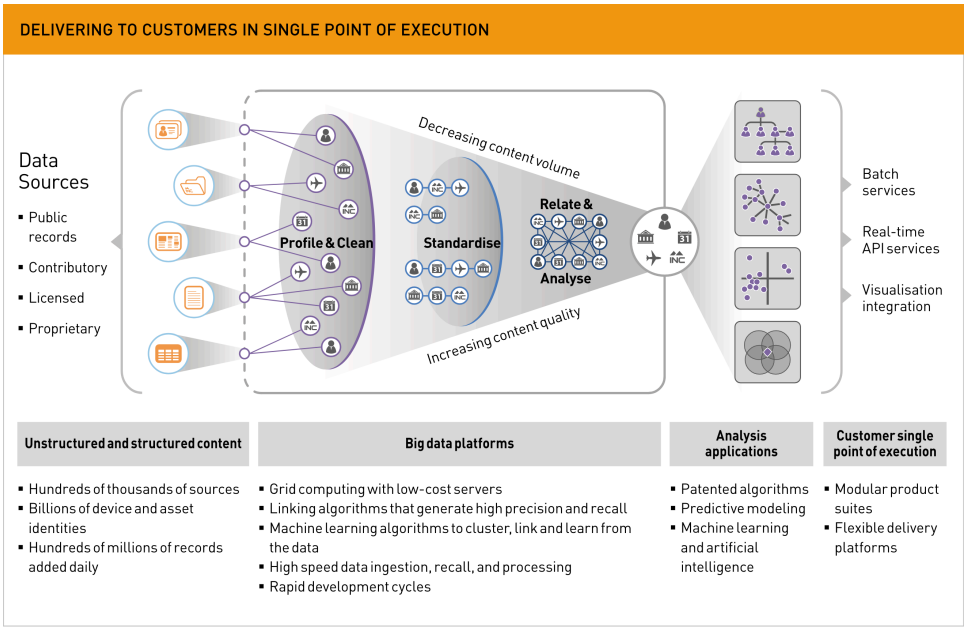


Figure 1: In its 2022 Annual Report, RELX describes its business model as ingesting large quantities of data, linking them together, and deriving platforms from them. [39]

While to any individual market segment or class of customers RELX and its subsidiaries might look like a portfolio of separate platforms and applications, one can only make sense of the company by thinking of each of them as a view on an interconnected graph of data[11]. Each additional source of data, either by acquiring new companies or by expanding their existing control of informational access points has the potential to create some combinatorically new set of opportunities for new platforms.

[11] Though apparently they have had historical difficulty actually getting that integration to work [40] .

For example, RELX is able to gather surveillance data on researcher attention data through the tracking in its ScienceDirect and Mendeley platforms. It also collects a large amount of chemical data through its control of scientific publishing that it rents access to on its Reaxys platform, which is supplemented by its LexisNexis (another RELX subsidiary) PatentSight database of patents. So far so normal.

What about the other sides of the multisided market? RELX is able to combine these and other data sources into new product. For pharmaceutical R&D companies, their bespoke Drug Design Optimization services advertise being able to use chemical, disease, and literature-based data to generate a priority list of potential therapeutic targets and drugs, as well as provide "competitive intelligence" about which targets are currently being studied, presumably identified from their ownership of the scientific literature coupled with surveillance data. Since clinicians don't trust pharmaceutical advertisements [41] , Elsevier uses its position as a perceived neutral third party to repackage advertisements as informational systems [42] , "journal-branded webinars," as well as a number of other avenues via its "360 degree advertising solutions" catalogue. So, by combining several data sources and platforms, Elsevier is able to offer pharmaceutical companies recommendations for candidate drugs above and beyond what would be possible with chemical information alone and then advertise their drugs directly to doctors.

Derivative platforms beget derivative platforms, as each expands the surface of dependence and provides new opportunities for data to capture. Its integration into clinical systems by way of reference material is growing to include electronic

health record (EHR) systems, and they are "developing clinical decision support applications [...] leveraging [their] proprietary health graph" [39] . Similarly, their integration into Apple's watchOS to track medications indicates their interest in directly tracking personal medical data.

That's all within biomedical sciences, but RELX's risk division also provides "comprehensive data, analytics, and decision tools for [...] life insurance carriers" [39] , so while we will never have the kind of external visibility into its infrastructure to say for certain, it's not difficult to imagine combining its diverse biomedical knowledge graph with personal medical information in order to sell risk-assessment services to health and life insurance companies. LexisNexis has personal data enough to serve as an "integral part" of the United States Immigration and Customs Enforcement's (ICE) arrest and deportation program [43, 44] , including dragnet location data [45] , driving behavior data from internet-connected cars [46] , and payment and credit data as just a small sample from its large catalogue [47] of data aggregated and linked into comprehensive profiles [48] . The contemporary knowledge graph-powered surveillance conglomerate gains its versatility precisely from its ability to span many unrelated domains and deploy new platforms as opportunities present themselves. As new data sources are acquired, the combinatorics of possible surveillance products correspondingly explode.

This pattern is true across the information industry [30] . A handful of representatives from Microsoft, Google, Facebook, eBay, and IBM describe some elements of each of their knowledge graphs in a 2019 paper [26] . Each has different scopes, applications, and interaction with the other data and processing infrastructure at the company, but all emphasize the ability for their knowledge graphs to accommodate change, heterogeneity, conflicting data, inference, and facilitate work by distributed teams due to their self-documenting and modular nature. Neo4j, developers of an eponymous graph database library, describes in one case study among its hundreds of customers how the U.S. Army uses its "connected data" to track its equipment and estimate the cost of some new exploratory imperialism [49] . An analysis of Palantir's hundreds of patents for knowledge graph technology (eg. [50, 51, 52, 53]) describes its ambitions for its knowledge graph:

> There is evidence [...] that Palantir has infrastructural aspirations to become a general classification system for data integration [...] that can be tailored into a universal knowledge graph. [...] Palantir similarly imagines a world where its platform might serve as a "shadow" universal knowledge graph for governments, industries, and organizations. [54]

Knowledge graphs *as a technology* - like all technologies - are not intrinsically unethical. It is the structure of the capital-K capital-G Knowledge Graph in its particular construction as a set of property and power relationships set against the context of the platform web that is pathological. They represent the historical trajectory of semantic web ideas and technologies from something that we are intended to use and create directly into privately held data that we can only interact with through platforms. They are coproductive with the corporate and technical structure of surveillance capitalism, facilitating conglomerates that gobble up as many platforms and data sources as possible to stitch them into an expanding, heterogeneous graph of data.

In particular, it is their "graph plus compute" structure - where some underlying graph of data is coupled with a set of algorithms and interfaces to view it - that is necessary to understand some of the more counterintuitive motivations of surveillance conglomerates. This structure complicates questions of "openness" versus "proprietariness," and provides a different lens on ostensibly "open" or "public" knowledge graph-based infrastructure projects.

3 Public Graphs, Private Profits

3.1 Unqualified Openness Considered Harmful

If the problem is information conglomerates stockpiling a massive quantity of proprietary data and renting use of it, isn't "open data" the answer? "Openness," including open source, open standards, and open data, is a subtle tool that can be used both to dissolve and reinforce economic and political power and is particularly ill-suited as a counter-strategy for corporate knowledge graphs .

Free and open source software, with its noble (and decidedly non-monolithic [55]) goal of creating an ecosystem of free[12] software, is a means by which large information companies can harvest the commons and outsource labor costs [56, 57, 58, 59, 60] . There are countless examples of FOSS developers maintaining software widely used by companies making billions of dollars for little or no compensation - eg. core-js [61] , OpenSSL [62] , leftpad [63] , PLC4X [64] and so on. When an information company releases or supports an open source project it is rarely an act of altruism. The effect is to prevent another company from profiting from a proprietary version of that technology, signal virtue, drive recruitment, and create a centralized point to concentrate donated labor. Microsoft, a famously good actor in software, took this several steps further with GitHub, VSCode, and later Copilot, capturing a large chunk of the software development *process* in order to trick programmers to be the "humans in the loop" refining the neural network to write code and dilute their labor power [65, 66, 67, 68] .

[12] "free as in whatever will prevent you from @'ing me about getting some definition of free wrong."

"Peer production" models, a more generic term for public collaboration that includes FOSS, has similar discontents. The related term "crowdsource[13]" quite literally describes a patronizing means of harvesting free labor via some typically gamified platform. Wikipedia is perhaps the most well-known example of peer production[14], and it too struggles with its position as a resource to be harvested by information conglomerates. In 2015, the increasing prevalence of Google's information boxes caused a substantial decline in Wikipedia page views [71, 72] as its information was harvested into Google's knowledge graph, and a "will she, won't she" search engine arguably intended to avoid dependence on Google was at the heart of its 2014-2016 leadership crisis [73, 74] . While shuttering Freebase, Google donated a substantial amount of money to kick-start its successor [75] Wikidata, presumably as a means of crowdsourcing the curation of its knowledge graph [76, 77, 78] .

[13] For critical work on crowdsourcing in the context of "open science," see [69] , and in the semantic web see [70] .

[14] I have written about the peculiar structure of Wikipedia among wikis previously, section 3.4.1 - "The Wiki Way" [1]

"Open" standards are yet another fraught domain of openness. For an example within academia, the seemingly-open Digital Object Identifier (DOI) system was concocted as a means for publishers to retain control of indexing research, avoiding the impact of the proposed free repository PubMedCentral and the high overhead of linking documents between publishers[15] (see sec. 3.1.1 in [1]). The nonprofit standards body NISO's standards for indicating journal article versions [80] and licensing [81] are used by publishers to enforce their intellectual property monopolies and programmatically scour the web to prevent free access to publicly funded information [82] .

[15] "The potential benefit of the service that would become CrossRef was immediately apparent. Organizations such as AIP and IOP (Institute of Physics) had begun to link to each other's publications, and the impossibility of replicating such one-off arrangements across the industry was obvious. As Tim Ingoldsby later put it, **'All those linking agreements were going to kill us.'**" [79]

Schema.org, a standard intended to be the generic interchange ontology of the web, is another emblem of enclosure of the semantic web. Its introduction at the SemTech 2011 conference was cause for a rare point of agreement[16] between the then-warring maintainers of RDFa and Microformats: "folks, it's wrong for Google to dictate vocabularies, let's not lose sight of that" [83] . Though ostensibly open, its structure and emphases have been roundly criticized, eg. having a eurocentric bias towards commercially valuable information [84] . It encourages website maintainers to embed Schema.org annotations in their pages in exchange for a boost in search rankings — which Google then embeds in its infoboxes, driving down page views. More fundamentally it cements the notion that Linked Data is something that we are only intended to use to make our information more available to some search engine crawler rather than make use of for ourselves: "In general, the de-

[16] (Intervening messages in the chat log have been omitted for clarity):

> `<tantek>` Hey Kavi - do you see what you've done here?
> `<tantek>` You've gotten a community leader of microformats.org (myself) and chair of W3C RDFa WG to *agree*
> `<edsu>` tantek: see, that's progress :)
> `<manu-db>` Yes - both RDFa and Microformats communities agree - sky will be falling, next.

sign decisions place more of the burden on consumers of the markup" [85] . It encodes the notion that there should be one "neutral" means of representing information for one (or a few) global search engines to understand, rather than for local negotiation over meaning. According to the transcribed Q&A after its 2011 announcement, the Google representatives characterized the creation of authoring tools like those created to make creative use of HTML more accessible as a potential "alternative path," but then dismissed the notion of improved tooling as "impossible" [86] .

Clearly, on its own, mere "openness" is no guarantee of virtue, and socio-technological systems must always be evaluated in their broader context: *what is open? why? who benefits?* Open source, open standards, and peer production models do not inherently challenge the rent-seeking behavior of information conglomerates, but can instead facilitate it.

In particular, the maintainers of corporate knowledge graphs want to reduce labor duplication by making use of some public knowledge graph that they can then "add value" to with shades of proprietary and personal data (emphasis mine):

> In a case like IBM clients, who build their own custom knowledge graphs, **the clients are not expected to tell the graph about basic knowledge.** For example, a cancer researcher is not going to teach the knowledge graph that skin is a form of tissue, or that St. Jude is a hospital in Memphis, Tennessee. This is known as **"general knowledge,"** captured in a general knowledge graph. **The next level of information is knowledge that is well known to anybody in the domain**—for example, carcinoma is a form of cancer or NHL more often stands for non-Hodgkin lymphoma than National Hockey League in some contexts it may still mean that—say, in the patient record of an NHL player). **The client should need to input only the private and confidential knowledge** or any knowledge that the system does not yet know. [26]

The creation of a collection of more domain-specific ontologies and tooling for ingesting previously unstructured data would allow for a new kind of globally linked knowledge graph ecosystem — making use of a broader range of publicly-available data, as well as facilitating new markets for renting access to interoperable data. Five information conglomerates conclude their joint paper on knowledge graphs accordingly:

> The natural question from our discussion in this article is whether different knowledge graphs can someday share certain core elements, such as descriptions of people, places, and similar entities. [26]

Having such standards be under the stewardship of ostensibly neutral and open third-parties provides cover for powerful actors exerting their influence and helps overcome the initial energy barrier to realizing network effects from their broad use [87, 88] . Peter Mika, the director of Semantic Search at Yahoo Labs, describes this need for third-party intervention in domain-specific standards:

> A natural next step for Knowledge Graphs is to **extend beyond the boundaries of organisations,** connecting data assets of companies along business value chains. This process is still at an early stage, and **there is a need for trade associations or industry-specific standards organisations to step in,** especially when it comes to developing shared entity identifier schemes. [89]

As with search, we should be particularly wary of information infrastructures that are *technically* open[17] but embed design logics that preserve the hegemony of the organizations that have the resources to make use of them. The existing organization of industrial knowledge graphs as chimeric "data + compute" models give a hint at what we might look for in public knowledge graphs: the data is open, but to make use of it we have to rely on some proprietary algorithm or cloud infrastructure.

[17] Go ahead, try and make your own web crawler to compete with Google - all the information is just out there in public on the open web!

Unfortunately, that is exactly what at least two US Federal agencies have in mind: the NIH and NSF are both in the thick of engineering cloud-based knowledge graph infrastructures and domain-specific ontologies with all the trappings of technology that fills the stated needs of information conglomerates at the expense of the people it is outwardly intended to serve. I assume that the researchers and engineers working on these projects are doing so with the best of intentions. The object of criticism is not the individuals within these projects, but the ideologies and systems they are embedded within. I will describe those efforts and their already apparent harms as a way of understanding how these technologies illustrate and reinforce the dominance of the existing corporate informational ecosystem — and to articulate an alternative.

3.2 NIH: The Biomedical Translator

Note:

This section is reproduced from, focuses, and expands on "Linked Data or Surveillance Capitalism?" from [1] .

The NIH's Biomedical Data Translator[18] project was initially described in its 2016 Strategic Plan for Data Science as a means of translating between biomedical data formats:

> Through its Biomedical Data Translator program, the National Center for Advancing Translational Sciences (NCATS) is supporting research to develop ways to connect conventionally separated data types to one another to make them more useful for researchers and the public. [90]

The original funding statement from 2016 is similarly humble, and press releases through 2017 also speak mostly in terms of querying the data – though some ambition begins to creep in. By 2019, the vision for the project had shifted from *translating* between data types into the realm of heterogeneous linkages in some meta-level system for linking and *reasoning* over them.

In their piece "Toward a Universal Biomedical Translator," then in a feasibility assessment phase, the members of the Translator Consortium assert that universal translation between biomedical data is impossible[19][91] . The impossibility they saw was not that of conflicting political demands on the structure of organization (as per [92]), but of the sheer quantity of the data and vocabularies needed to describe them. The risk posed by a lack of a universal "language" was not being able to index all possible data, rather than inaccuracy or inequity[20].

Undaunted by their stated belief in the impossibility of a universalizing ontology, the Consortium created one in their biolink model[21] [95, 94] . Biolink consists of a hierarchy of general[22] classes: eg. a BiologicalEntity like a Gene, or a ChemicalEntity like a Drug. Classes can then linked by any number of properties, or "Slots[23]."

Biolink was designed to be a sort of "meta ontology," or a means of mapping different domain-specific biomedical ontologies onto a common vocabulary[24]. As a meta-ontology, Biolink is targeted towards "meta-data." Rather than accommodating "raw data[25]," Biolink is expected to operate at the level of "knowledge," or "generally accepted, universal assertions derived from the accumulation of information" [98] : this procedure treats that disease, this chemical interacts with that one, etc.

The primary way Biolink is used within the Translator is to structure a registry of database APIs, each called a "Knowledge Source." Knowledge Sources use Biolink to declare that they are able to provide assertions about a particular set of classes or slots, like drugs that affect genetic expression, which makes them part of the Translator's distributed Knowledge Graph. The Translator project, in this universalizing impulse, recapitulates some of the early beliefs of the Semantic Web updated with some of the techniques of Linked Data.

[18] Or, just "Translator"

[19]

> First, we assert that a single monolithic data set that directly connects the complete set of clinical characteristics to the complete set of biomolecular features, including "-omics" data, will never exist because the number of characteristics and features is constantly shifting and exponentially growing. [...] We also assert that there is no single language, software or natural, with which to express clinical and biomolecular observations—these observations are necessarily and appropriately linked to the measurement technologies that produce them, as well as the nuances of language. The lack of a universal language for expressing clinical and biomolecular observations presents a risk of isolation or marginalization of data that are relevant for answering a particular inquiry, but are never accessed because of a failure in translation.
> Based on these observations, our final assertion is that automating the ability to reason across integrated data sources and providing users who pose inquiries with a dossier of translated answers coupled with full provenance and confidence in the results is critical if we wish to accelerate clinical and translational insights, drive new discoveries, facilitate serendipity, improve clinical-trial design, and ultimately improve clinical care. This final assertion represents the driving motivation for the Translator system. [91]

[20] In an odd mixture of metaphors, members of the Translator consortium introduced the project with a piece titled "Deconstructing the Translational Tower of Babel." [93] . It is unclear why an effort to create a universalizing ontology would be deconstructing a tower of babel, as in one common interpretation it was the hubristic power of a unified language that caused it to be built and incurred the wrath of God. But I digress.

[21] The title of the Biolink paper is "Biolink Model: A universal schema for knowledge graphs in clinical, biomedical, and translational science" [94]

[22] General as opposed to an ontology like MONDO [96] that identifies specific diseases.

[23] or links, labeled edges, predicates. The terminology is more or less interchangeable.

[24] To their credit, the Translator project seems to have made some of the long-delayed tooling for declaring a schema in a more accessible syntax than RDFS/OWL and generating representations in multiple formats, from JSON-LD to pydantic models. The Biolink paper also mentions a "Node Normalization Service" for being able to resolve Linked Data entities from different vocabularies that have been declared to be the same thing, but at the time of writing development seems to have slowed

[25] In a 2018 presentation by one of Biolink's authors: "What NOT to use the biolink-model for: Raw data, Metadata about a dataset" with some caveat that the underlying metamodel might still be useful [97] .

This structure strongly constrains who is intended to be able to contribute to the Translator: highly curated biomedical informatics platforms, rather than basic researchers or the public at large. NIH RePORTER shows a series of grants for small councils of experts to create domain-specific ontologies and Knowledge Sources. This, in turn, reflects deeper beliefs about the nature of information within the Translator ecosystem: "knowledge" is not a social, contextual, or dialogical phenomenon, but a "natural resource" that can be mined from information that is "out there." A scientific paper is a neutral carrier of a factual link between entities. The meaning of "translation," in some uses, has shifted from translating *between data formats*, to *"translating information into knowledge"* [91] . This is, of course, the ideology of Big Data: "when heterogeneous networks are connected at a massive scale, new knowledge can be extracted as an emergent property of the network" [99] . The Translator seems to imagine its project as a refinery, converting crude data into Knowledge that can fuel platforms.

The platforms that the translator imagines are those where clinicians or researchers can pose plain language queries and have answers returned by some algorithmic "reasoning agent" that aggregates data from multiple Knowledge Providers and synthesizes a response [94, 100, 101, 102, 103] . We are not intended to look too closely at the data from Knowledge Providers, as it is likely to be incomplete or conflicting.

Several pilot experiments have demonstrated combining some aggregated patient records with the broader knowledge graph in order to eg. identify new risk markers for disease [99, 104, 105, 106] . These systems layer personal records underneath "general" biomedical information like drug interactions and biological processes and use the extended information from the graph to infer information both about the nature of the disease and the patient. A platform integrated with the UCSF electronic health record system that layers disaggregated clinical records under the general knowledge graph is already apparently in a state of mature development [107] .

It is only with the inclusion of patient records into the knowledge graph that it becomes possible to use in a clinical setting: for even basic queries like "which drugs treat this disease" one has to be aware of patient qualities like allergies and comorbid conditions. To know how to treat the generic diagnosis of "gender dysphoria," one needs to know which gender the patient is experiencing dysphoria about. The logic of knowledge graph makes it not just hungry for *some* personal medical data, the promise is that more data **always** improves its results[26].

[26] The answer to a question posed as an algorithmic problem is always more data: "These results suggest that if more EHR concepts were mapped to SPOKE, a significant improvement in the classifier could be achieved." [104]

Why might we be critical about the NIH funding a series of projects to unify biomedical and personal health data in some universalized, platformatized knowledge graph? In short: because it won't work as intended, its partially-working components will have immediately harmful results, and it will inevitably be captured by the surveillance industry.

First, as with any machine-learning based system, the algorithm can only reflect the implicit structure of its creation, including the beliefs and values of its architects [108, 109] , its training data and accompanying bias [110] , and so on. The "mass of data" approach ML tools lend themselves to, in this case, querying hundreds of independently operated databases, makes dissecting the provenance of every entry from every data provider effectively impossible. For example, one of the providers, mydisease.info was more than happy to respond to a query for the outmoded definition of "transsexualism" as a disease [111] along with a list of genes and variants that supposedly "cause" it - see for yourself. At the time of the search, tracing the source of that entry first led to the disease ontology DOID:1234, which has an official IRI, but in this case was being served by a graph aggregator Ontobee (Archive Link), which in turn listed this unofficial GitHub repository **maintained by a single person** as its source[27]. This is, presumably, the fragility and inconsistency in input data that the machine learning layer is intended to putty over.

[27] I submitted a pull request to remove it, and a full year later it was merged!

If the graph encodes being transgender as a disease, it is not farfetched to imag-

ine the ranking system attempting to "cure" it. A seemingly pre-release version of the translator's query engine, ARAX, does just that: in a query for entities with a `biolink:treats` link to gender dysphoria[28], it ranks the standard therapeutics [112, 113] Testosterone and Estradiol 6th and 10th of 11, respectively — behind a recommendation for Lithium (4th) and Pimozide (5th) due to an automated text scrape of two conversion therapy papers[29]. Queries to ARAX for treatments for gender identity disorder helpfully yielded "zinc" and "water," offering a paper from the translator group that describes automated drug recommendation as the only provenance [114] . A query for treatments for `DOID:1233` "transvestism" was predictably troubling, again prescribing conversion therapy from automated scrapes of outdated and harmful research. The ROBOKOP [115] query engine behaved similarly, answering [a query for genes associated with]({{ "/data/ROBOKOP_message.json" | relative_url }}) gender dysphoria with exclusively trivial or incorrect responses[30].

It is critically important to understand that with an algorithmic, graph-based precision medicine system like this **harm can occur even without intended malice.** The power of the graph model for precision medicine is precisely its ability to make use of the extended structure of the graph[31]. The "value added" by the personalized biomedical graph is being able to incorporate the patient's personal information like genetics, environment, and comorbidities into diagnosis and treatment. So, harmful information embedded within a graph — like transness being a disease in search of a cure — means the system either a) incorporates that harm into its outputs for seemingly unrelated queries or b) doesn't work. This simultaneously explodes and obscures the risk surface for medically marginalized people: the violence historically encoded in mainstream medical practices and ontologies (eg. [111, 116] , among many), incorrectly encoded information like that from automated text mining, explicitly adversarial information injected into the graph through some crowdsourcing portal like this one [117] , and so on all presented as an ostensibly "neutral" informatics platform. Each of these sources of harm could influence both medical care and biomedical research in ways that *even a well-meaning clinician might not be able to recognize.*

The risk of harm is again multiplied by the potential for harmful outputs of a biomedical knowledge graph system to trickle through medical practice and re-enter as training data. The Consortium also describes the potential for ranking algorithms to be continuously updated based on usage or results in research or clinical practice[32] [91] . Existing harm in medical practice, amplified by any induced by the Translator system, could then be re-encoded as implicit medical consensus in an opaque recommendation algorithm. There is, of course, no unique "loss function" to evaluate health. One belief system's vision of health is demonic pathology in another. Say an insurance company uses the clinical recommendations of some algorithm built off the Translator's graph to evaluate its coverage of medical procedures. This gives them license to lower their bottom line under cover of some seemingly objective but fundamentally unaccountable algorithm. There is no need for speculation: Cigna already does this [118] . Could a collection of anti-abortion clinics giving one star to abortion in every case meaningfully influence whether abortion is prescribed or covered? Why not? Who moderates the graph?

The centralized structure of the Translator's Knowledge Providers and query engines make a small group of experts responsible for curating the entire structure of biomedical information. The curation process could be "crowdsourced" to allow affected communities to suggest improvements, but the platformatized nature of the Translator both concentrates decisionmaking power and diffuses responsibility across a string of platform holders. Who is supposed to fix incorrect or harmful query responses? Is it the responsibility of the potentially dozens of Knowledge Providers, the swarm of reasoning agents, or the frontend wrapper you pay a monthly subscription for? It is the platformatized nature of the Translator itself that creates the need for centralized moderation in the first place. The design of the Translator to evolve into a series of "user-" or customer-facing platforms that aspire to universality binds it to all the regulatory burden any biomedical technology

[28] To its credit, ARAX does transform the request for `DOID:10919` to `MONDO:0001153` - gender dysphoria.

[29] as well as a recommendation for "date allergenic extract" from a misinterpretation of "to date" in the abstract of a paper that reads "Cross-sex hormonal treatment (CHT) used for gender dysphoria (GD) could by itself affect well-being without the use of genital surgery; however, **to date,** there is a paucity of studies investigating the effects of CHT alone"

[30] ITSN2 was identified in an unrelated paper about attachment patterns, HSD17B3 and 5a-RD2 were incorrectly identified as HSD17B13 and DHRS11 from another paper, POMC and OPN1SW were sourced from two papers that don't mention them. Androgen receptors were also identified, which is probably true, but almost trivially so.

[31] eg. Some members of the SPOKE project, a Knowledge Provider for the Translator project, describe the effects of the extended graph as "pushing" or influencing the "flow" of information:

> "For this patient, information flows from Carbamazepine to a set of Disease nodes (either through "treated by" or "contraindicated for" edges) and then (either directly or through an additional Disease or Gene node) to the genes CNP, MAG, or PTEN which are all components of "Myelin sheath adaxonal region." [104]

[32]

> "The Reasoners then return ranked and scored potential translations with provenance and supporting evidence. The user is then able to evaluate the translations and supporting evidence and provide feedback to the Reasoners, thus promoting continuous improvement of the prototype system." [91]

bears. The cost of moderation will of course be enormous, placing a fundamental constraint on its lifespan as a publicly funded project — and a strong incentive towards co-option by the information conglomerates capable of paying it[33].

These problems hint at the likely fate of the Translator project. Rather than integrating into the daily practice of researchers, the centralized process of creating Knowledge Providers can only be maintained for as long as the grant funding for the Translator project lasts. When queried at the time of writing, of the 25 knowledge providers that were responsive to information about "Anything that is related to the common cold," 22 were unresponsive or timed out.

How the Translator is intended to work by its architects is almost irrelevant compared to the question of what happens to it *after the project ends.* Linking biomedical and patient data in a single platform is a natural route towards a multisided market where records management apps are sold to patients, treatment recommendation systems are sold to clinicians, research tools and advertising opportunities are sold to pharmaceutical companies, risk metrics are sold to insurance companies, and so on. The contours of this market are already clear.

As a non-exhaustive set of examples:

- I have already described **RELX**'s interest in personal biomedical data. Their 2022 Annual Report [39] is the first year where they explicitly describe their entrance into the patient data market[34]. RELX is a particularly worrying example because of their established roles among academics, governmental entities, medical systems, and insurance providers.
- **Amazon** already has a broad home surveillance portfolio [121] , and has been aggressively expanding into health technology [122] and even literally providing health care [123, 124] , which could be particularly dangerous with the uploading of all scientific and medical data onto AWS with entirely unenforceable promises of data privacy through NIH's STRIDES program [125] .
- **Google** already includes medical conditions in its surveillance-backed advertising profiles [126, 127] , and is edging its way into wearable health data with eg. its acquisition of FitBit [128] . It also already has a system, Med-PALM, for biomedical question answering based on large language models [129, 130, 131] . Search is a primary entrypoint for many people seeking health information, and Google presumably would be more than happy to merge that data with a generalized biomedical knowledge graph.
- **Apple** already has a matured Health ecosystem of apps and services for both patients, clinicians, and researchers [132, 133] and has a similar exposure to relevant data and control of platforms (iOS, watchOS) to make use of it, though they have marketed themselves in the surveillance space as a defender of privacy.
- Of course **Microsoft** [134] and **IBM** [135] are also in play.

The design of the Translator project reflects the prevailing logic of the surveillance economy as powered by knowledge graphs, and is poised to be swallowed up by it. Rather than a means for us to collectively make sense together, it imagines a cloud-driven system where a small group of experts wave a wand of unknowable algorithms over a bulging plastic trash bag of data to pull out the Magic Knowledge Rabbit. The noble intention of making a generalized biomedical knowledge graph for the public good is unlikely to be realized. In the process, though, the NIH will have funded facilitating technologies and standards for the merger of personal electronic health records with the broader landscape of biomedical data. Academics will have new vectors by which they become unwitting or unwilling collaborators[35] with surveillance and data brokers, lending what credibility they have left to a landscape of buggy black boxes of biopolitical control. And, most importantly, vulnerable populations will have dozens of new ways to be marginalized by

[33] There is a clear analogy to the recent push to increase internet content regulation by social media companies [119] . A platform makes a quasi-universal social space for profit, moderation then has to scale with the size of the platform, then it lobbies to increase regulatory burden to a point that is impossible to maintain for all but already-scaled companies. It is only the quasi-universality of the platform that makes the moderation burden so high in the first place, however, compared to eg. a decentralized medium that might have a structurally different disposition to moderation (see [120]).

[34] "In commercial healthcare, identity, claims and provider data is combined with patient information to assist healthcare providers, pharmacies and insurers in delivering improved health outcomes, ensuring accurate and complete provider data and regulatory compliance." [39]

[35] Although through the extremely cursed neoliberal lens of "tech transfer," many might be very willing.

the techno-political medical establishment.

3.3 NSF: Open Knowledge Network

While the NIH builds a set of universal knowledge graphs for biomedical information, the NSF is building them for everything else. Its Open Knowledge Network (OKN) project intends to "provide an essential public-data infrastructure for enabling an AI-driven future." [136] Compared to the Translator, the OKN pulls punches for neither its utopian promises nor obvious risks. Some sections of its roadmap are written in the breathless tenor of Big Data solutionism, claiming that "harnessing the vast amounts of data generated in every sphere of life and transforming them into useful, actionable information and knowledge is crucial to the efficient functioning of a modern society" [136] . Without mincing words, the OKN intends to make a Universal Knowledge Graph of Everything. The recipe is familiar: a) make authoritative schemas for everything, b) link them all together, c) ingest data from as many sources as possible at whatever quality available, d) integrate private with public data e) put it all in the cloud! (p. 18-19 "Creating an OKN" [137]).

The project was initially proposed in 2017, went through two cohorts of projects within the NSF Convergence Accelerator in 2019 and 2020[36], and invited a broader submission of proposals in November 2021 [139] . The roadmap comes at the end of a series of workshops in 2022 intended to scope and outline the OKN so there is still very little public evidence of its progress to evaluate[37], but along with the Translator, what is available tells the story of an emerging consensus for public data infrastructures.

Its domain is much broader than the Translator, and is unmistakably bound up in both the United States Federal Government's military and political interests in Artificial Intelligence[38] [143] and the information economy's interests in making a universal space where all information can be bought and sold with minimal friction[39] [137] . Where the Translator has the near-inevitable risk of being captured by information conglomerates, through the euphemism of "public private partnership" the OKN makes clear it intends capture by for-profit entities as part of its design: for example, the team behind the SPOKE biomedical knowledge network immediately spun off a for-profit startup to sell the graph as a cloud service [144] , abandoning further UX development of its publicly accessible demo.

They OKN describes its work along "vertical" and "horizontal" dimensions, where "vertical" applications refer to specific uses or domains like energy or health data, and "horizontal" themes like technologies and governance are shared across all domains. The collection of "vertical" topics identified in the 2022 roadmap hint at the effectively unbounded scope of the OKN: accelerated capitalism via supply chain logistics, more tightly integrated weapons development, a handful of climate change projects, an omniscient financial system, and so on. Each imagines the primary problem in a given domain not as structural exploitation or injustice, but a lack of data[40].

The "vertical" topical working groups in the 2022 roadmap centered on an algorithmic justice system are particularly illustrative: An **Integrated Justice Platform** group describes the need for greater surveillance across every contact people have with the US Justice System in a wish list of data sources that should be integrated - arrest and booking, jail, trial, prosecution, and the rest. A **Decarceration** group[41] describes extending that surveillance through to the rest of incarcerated people's lives after they are released - rehab, parole, foster care, shelters, public services, etc. A **Homelessness** group intends to track unhoused people in order to match them to available resources. A **Decision Support for Government**[42] group describes bundling up these and other data sources into platforms for making "data driven decisions" on topics including crime and policing.

On their own, each of these groups describes noble goals: decreasing bias in the

[36] The Convergence Accelerator is a project specifically designed to provide public research funding to for-profit industries [138]

[37] SPOKE, discussed previously, was funded by both the Translator project [140] and OKN [141] , and KnowWhereGraph is another notable early prototype [142]

[38] The Open Knowledge Network is described in the National Security Commission on Artificial Intelligence's Final Report, an "integrated national strategy to reorganize the government, reorient the nation, and rally our closest allies and partners to defend and compete in the coming era of AI-accelerated competition and conflict," as part of a strategy to maintain US AI research competitiveness in the "race for AI supremacy" against (primarily) China [143] .

[39] The Big Data Interagency Working Group's 2017 workshop summary describes the desire for the OKN as a way to overcome "walled gardens" in existing commercial knowledge graphs so that future AI-powered technologies can benefit from "synergies that use both open and proprietary data," specifically to power "conversational" knowledge services, which we will discuss in the next section. [137]

[40] A recurring pattern in techno-solutionism:

> "These perspectives assume that complex controversies can be solved by getting correct information where it needs to go as efficiently as possible. In this model, political conflict arises primarily from a lack of information. If we just gather all the facts, systems engineers assume, the correct answers to intractable policy problems like homelessness will be simple, uncontroversial, and widely shared.
> But, for better or worse, **this is not how politics work.**" [145]

[41] Including a representative from Booz Allen Hamilton, which may be familiar as the former employer of Edward Snowden, who was working for them on a contract with the NSA which gave him access to the details of its PRISM mass-surveillance program.

[42] See [146] for discussion of algorithmic governance in a "smart city."

justice system, providing resources to formerly incarcerated or unhoused people, making government decisions more efficient. Taken together, however, the projects describe a panoptical surveillance system that wouldn't even need to be reconfigured to be used for algorithmically-enhanced oppression. I doubt any of the researchers in these groups intend for their work to be used for state violence, but *Palantir doesn't care what academics intended their tools to be used for*[43].

The motivations behind integrating government data sources and automating public benefit delivery cannot overcome the context of systemic oppression they are embedded within. Group H, the "Homelessness OKN" group, takes particular effort[44] to focus on the needs of the unhoused and address the potential risks of "track[ing] homelessness in real time, [and] identify[ing] available homelessness programs and services," but misses the already-real harms of similar prior efforts. Virginia Eubanks describes how Los Angeles County's Coordinated Entry System — a program very much like that described by group H, intended to match unhoused people with housing supply by integrating previously siloed data systems — operates as a sophisticated mechanism of control and punishment:

> For Gary Boatwright and tens of thousands of others who have not been matched with any services, coordinated entry seems to collect increasingly sensitive, intrusive data to track their movements and behavior, but doesn't offer anything in return. [...] Moreover, the pattern of increased data collection, sharing, and surveillance reinforces the criminalization of the unhoused, if only because **so many of the basic conditions of being homeless are also officially crimes.** [...] The tickets turn into warrants, and then law enforcement has further reason to search the databases to find "fugitives." Thus, **data collection, storage, and sharing in homeless service programs are often starting points in a process that criminalizes the poor.** [...]
>
> Further integrating programs aimed at providing economic security and those focused on crime control threatens to turn routine survival strategies of those living in extreme poverty into crimes. **The constant data collection from a vast array of high-tech tools wielded by homeless services, business improvement districts, and law enforcement create what Skid Row residents perceive as a net of constraint that influences their every decision.** Daily, they feel encouraged to self-deport or self-imprison. Those living outdoors in encampments feel pressured to constantly be on the move. Those housed in SROs or permanent supportive housing feel equally intense pressure to stay inside and out of the public eye. [...] **Coordinated entry is not just a system for managing information or matching demand to supply. It is a surveillance system for sorting and criminalizing the poor.** [145]

It is impossible to consider integrated data in government without confronting the reality of algorithmic policing. Under its Strategic Plan goal of "Realiz[ing] Tomorrow's Government Today" Los Angeles County has already been integrating its information systems, including creating a unified system of law enforcement and other public service data "to identify super utilizers of justice and health system resources"[45] [149, 150] . Many police departments — including the LAPD — already have access to the kind of linked data ecosystems described by the OKN by renting them from private data brokers like Palantir [147, 151] . These data infrastructures facilitate the well-described feedback loop of predictive policing, where areas already subject to historical economic and racist violence are classified as "high-crime areas," more police are concentrated there, in turn causing them to measure or create more crime[46] [147, 152, 154, 153, 155, 156, 157] . The reformist idea that more data will help us "police the police" is belied by the resolute history of more data allowing the police to innovate on information asymmetries to create new expressions of power [158, 159] .

The critical difference between prior infrastructures and those imagined by the OKN is that they are explicitly designed to be linked into a continuous network of data that enables the same kind of data-driven decisionmaking that drives predic-

[43] Palantir prides itself on its ability to continuously add new data sources:

> "Because one of Palantir's biggest selling points is the ease with which new, external data sources can be incorporated into the platform, its coverage grows every day. LAPD data, data collected by other government agencies, and external data, including privately collected data accessed through licensing agreements with data brokers, are among at least 19 databases feeding Palantir at JRIC." [147]

[44] The "Innovation Sprint" is essentially as an extended pitch session for future work, which is both important context as a strong counterincentive to serious ethical consideration of the projects — and also a demonstration of why it might not be good to organize infrastructural projects as pitch sessions rather than from some ethical foundation.

[45] ...and then outsourcing its maintenance to an external company along with liability in the case of a data breach [148]

[46]

> These visits often resulted in other, unrelated arrests that further victimized families and added to the likelihood that they would be visited and harassed again. In one incident, the mother of a targeted teenager was issued a $2,500 fine when police sent to check in on her child saw chickens in the backyard. In another incident, a father was arrested when police looked through the window of the house and saw a 17-year-old smoking a cigarette. These are the kinds of usually unreported crimes that occur in all neighborhoods, across all economic strata—but which only those marginalized people who live under near constant policing are penalized for. [152, 153]

tive policing for *any* system. We should not be imagining the utterly mechanistic bureaucracy of *Kafka* here, but rather the deeply expressive and personal exercise of power of Terry Gilliam's *Brazil.* Widespread algorithmic governance doesn't necessarily look like a faceless bureaucracy where all decisions are made by a computer, existing algorithmic systems like predictive policing and the working conditions at Amazon warehouses retain the very human domain of *discretion* (see [158]). The algorithms and seemingly open infrastructures of these two projects purport themselves as objective and egalitarian, but who they are built for, who gets to provides the inputs, and who decides which outputs matter make their reality very different.

A report from Wired and Lighthouse Reports that gained unprecedented access to an algorithmic social service system created by Accenture for the city of Rotterdam shows how the discretion of caseworkers and a purportedly "objective" algorithm together create a profoundly discriminatory system [160, 161] . Caseworkers make subjective determinations like an applicant showing signs of low self-esteem or whether they can "deal with pressure" and feed them along with characteristics like age and gender into an opaque set of decision trees to determine whether they should be investigated for benefits fraud. The opacity of the system makes it rich with opportunities for discretionary bias that, again, can be both intentional and unintentional. For example, the mere *presence* of a comment on motivation or attitude increases ones likelihood of being flagged for investigation, even if that comment is positive. Intentional and unintentional welfare fraud are undifferentiated in the training data, making language barriers — a source of accidental fraud from not understanding the system — a primary determinant of investigation. In the case of the OKN, merging data from many governmental systems under the aegis of algorithmic fairness could do precisely the opposite: expanding the points of discretionary control where opaque decisions in input data or application of an algorithm can have long range impacts on governmental outcomes.

While it is still too early to evaluate the OKN as a project, it along with the Translator show the outlines of public information infrastructures to come.

The two major public research funding agencies in the US have both devised novel funding mechanisms to be able to bypass typical review and include private industry in their data infrastructure projects [162, 138] . These data infrastructures consist of a number of sub-projects for building new domain-specific and universalizing Semantic Web ontologies and cloud-based platforms for data storage and retrieval. Both are both explicitly oriented towards exposing structured data to "AI" and other derivative "big data" applications, rather than towards integrating in the daily work of researchers or the public at large. The potential for harm from big data solutionism, corporate capture, and discretionary abuse is common to both projects. These and other[47] efforts like NIH's STRIDES initiative point towards a cloud-driven SaaS/PaaS future for public data infrastructure [166] .

[47] It's out of scope here, but another point of comparison and contrast is the EU's European Open Science Cloud (ESOC) project [163, 164, 165]

The Translator and OKN and their sub-projects have many possible fates: their grant funding could peter out and they could amount to very little beyond the scattered prototypes and spinoff startups that they've currently produced — a mere wasted opportunity. They could flourish and become exactly what their creators intend them to be - the seamless data infrastructures of the future that manage to miraculously avoid all potential harms.

More important than the outcomes of these projects in particular is how the ruts of collective imagination drive both projects towards very similar designs with very similar flaws. It is not the technologies *in themselves* that are pathological, but the way they are imagined as part of a larger socio-political system: who is intended to use them, to have power within them, to own them? These projects presuppose an enlightened technocrat class as the principle agent of social good and configure technologies accordingly. The grand unified graph of everything will allow

the truth to emerge from the Big Data so that decisionmakers can divine what is best for the commoners who could not possibly understand the complexities of their health, environment, or social systems themselves. This belief finds fertile ground among academics who intend to do good but have little incentive to critically evaluate the surrounding political-economic systems that might structure the form that good might take[48].

Maybe paradoxically, the aspirations of universality strongly constrain their ambition and use. By punting the more foundational questions of creating storage and compute infrastructure to the cloud, there is no place for "raw" data since it is too unwieldy to affordably host or handle. By recapitulating the focus of the early semantic web on universalizing ontologies rather than tooling for arbitrary expression, the projects hem themselves in to only what its creators can imagine either in the ontologies themselves or the ways their expansion are governed. By needing to present themselves as singularly "true" and reliable, they are less able to represent ambiguity and uncertainty — which are ultimately "truer" representations of most kinds of Knowledge. By adopting the patterns of the industries that enclose us within similarly limited platforms, they are doomed to re-entrench rather than liberate us from the engineered helplessness that makes it hard to fluidly express and make use of information in the first place.

These design logics and the technologies they produce must be understood against the backdrop of the history and present structure of the platformatized cloud-driven information economy writ large. Facing the limits of proprietary ontologies in private knowledge graphs, the information industry wants a set of cross-domain "top level" ontologies to enable the smooth interchange of public information that can then be integrated with "lower-level" private ontologies for an even greater array of surveillance-backed knowledge-as-a-service platforms. Under the guiding star of openness as an end in itself, researchers and funding agencies seem keen to provide it, and in partnership with private industry have adopted the logic of their platforms.

[48] For a fuller discussion of academic utopias, power, imagination, managerialism, and its intersections with corporate reality, see [167]

> The increasing interpenetration of government, university, and private firms has led all parties to adopt language, sensibilities, and organizational forms that originated in the corporate world. While this might have helped somewhat in speeding up the creation of immediately marketable products — as this is what corporate bureaucracies are designed to do — in terms of fostering original research, the results have been catastrophic. [...]
> A timid, bureaucratic spirit has come to suffuse every aspect of intellectual life. More often than not, it comes cloaked in a language of creativity, initiative, and entrepreneurialism. But the language is meaningless. The sort of thinkers most likely to come up with new conceptual breakthroughs are the least likely to receive funding, and if, somehow, breakthroughs nonetheless occur, they will almost certainly never find anyone willing to follow up on the most daring implications. [...]
> This is what I mean by"bureaucratic technologies": administrative imperatives have become not the means, but the end of technological development. [167]

4 Infrastructural Ideologies

The Cloud is not a neutral, inevitable, or optimal form of the web — it has been actively constructed to facilitate a particular set of power and property relationships that make up the web's dominant business model. It is supported by a system of *values* and *beliefs* that are consciously affirmed to various degrees in a positive feedback loop with the expertise and resource investment that make its enabling technologies more developed and obvious than alternatives, in turn fueling the truth of those beliefs, including that of the inevitability of the cloud model itself.

The history of the web is an odd substance: always present and eternal, yet profoundly ephemeral and immediately forgotten. It becomes increasingly difficult to imagine obscure roads not taken in the deeper architecture of the internet[49] with every fork. Before the dominance of compute in the cloud, distributed computing projects like folding@home were more powerful than any supercomputer[50] [169] . Before the dominance of cloud video streaming platforms, peer-to-peer systems accounted for a majority of global internet traffic: in the mid-2000's between 49% and 95%, depending on the survey [170, 171] .

The Cloud paradigm is at once phenomenally successful and riddled with obviously undesirable qualities. Cloud services promise large volumes of hassle-free storage — but also make our data take a round trip across the planet if we want to transfer it between computers in the same room. Cloud systems are impressive feats of engineering, capable of serving immense quantities of data from relay CDNs dotted around the globe — but only need to do so because of the preposterous inefficiency of needing to re-serve data like streaming video in full each time they are accessed. Cloud systems can be made to have very high uptime, but then

[49] Except by the scores of beloved nerds in exile on the freer parts of the internet who remember the death of IRC and RSS and the weaponization of JavaScript **acutely and personally.**

[50] During the first year of the COVID-19 pandemic a wave of folding@home volunteers broke the exascale computing barrier and made it more powerful than the top 100 supercomputers combined — filling a need that the cloud either *couldn't* or *wouldn't* [168] .

they do go down their dramatic centralization causes massive internet-wide blackouts even for systems that only depend on them indirectly [172, 173] . Delivering cloud platforms through the browser requires less setup than local software, but the complexity of the underlying web standards make it effectively impossible [174] to escape the near-monopoly[51] of Chrome[52], and make many services completely unavailable if the internet goes out or even slows down.

That these trade-offs are either not considered or seen as the natural constraints of internet technologies is precisely the evidence of The Cloud as ***ideology.*** By treating The Cloud as a system of *belief* we can better understand how its acolytes imagine the world they are creating — and what they have in store to get us there. In particular, it is only possible to understand the *meaning* and *intention* of the surge of **chatbots** like chatGPT, Microsoft's integration into Bing, and Google's Bard as the logical conclusion of both the Cloud Orthodoxy and the history of Knowledge Graphs as a universal acid in data infrastructures. Finally, reopening the avenues foreclosed by its structuring beliefs, we will propose an alternative in **Vulgar Linked Data.**

[51] The last major competitor being Firefox with market share in the low teens. Hang in there little fox!

[52] Which Google uses as a surveillance platform and a weapon which, according to unredacted court records detailing its "Privacy Sandbox" project, they plan to use for a forceful takeover of the rest of the global ad market in the name of privacy: "Google's new scheme is, in essence, to wall off the entire portion of the internet that consumers access through Google's Chrome browser." [175] .

4.1 The Cloud Orthodoxy

Ideology evades any singular definition, and I'm not obnoxious enough to claim I have a Complete and True Perspective[53] on something as multifarious as the belief system underlying The Cloud as an infrastructural pattern.

[53] Universal definitions are themselves part of of the critique.

To set the Terms and Conditions of this section: this definition is a necessary strawman to make sense of patterns of outcomes and pose as contrast to our alternative. I describe the Cloud Orthodoxy as a belief *system* because none of its components are unique or necessary for any one person to believe, but they are mutually reinforcing and self-compatible. It is one of many ideologies active in this cluttered space, including immortality cults like longtermism and good old fashioned neoliberalism. Many of these beliefs are not "bad" in themselves — assuming that the adherents of an ideology don't believe they are "bad" people is a foundational part of trying to understand them. By describing it as a positive vision, I am omitting the brutal reality of surveillance, control, and profit extraction that it generates. These ideas of course draw on a mountain of prior thought[54], and I admit my relative inexperience, welcome critique and contextualization, and will certainly need to completely rewrite them in future work.

[54] Eg. [92, 108, 109, 70, 176, 177, 178, 179]

My argument here is that the people and companies involved with these technologies don't have an "ethical deficit" that might call for "more ethics in AI," but that The Cloud poses its own strong ethical doctrine.

The Terms and Conditions having been settled...

A cardinal value of Cloud Orthodoxy is **convenience.** The internet should be *fast, reliable,* and everything[55] should be available on demand. Convenience is elevated at the exclusion of other values when in conflict like shared power or flexibility. **Complexity is a cognitive nuisance** for people with otherwise busy full lives, so it should be hidden as much as possible. **Interface design** is a major point of competition between platforms because it is a primary method of obscuring complexity.

[55] (that is profitable to maintain IP licenses for)

The world is **asymmetrical and hierarchical.** I am a consumer, a *user* and I trade my power to a *developer* or platform owner in exchange for convenience. The purpose of the internet is for platform holders to **provide services** to users. As a user I have a right to *speak with the manager,* but do not have a right to decide which services are provided or how. As a platform owner I have a right to demand whatever the users will give me in exchange for my services. Services are *rented* or given away freely[56] rather than *sold* because to the user the product is *convenience* rather than *software.* **Powerlessness is a feature:** users don't need to learn anything, and

[56] The notion of presenting services as free by virtualizing computing resources is as old as time sharing on digital computers, eg. Tung-Hui Hu relates this history to the creation of the atomized individual digital subject described below:

> "In this, time-sharing anticipated the way that the contemporary cloud encourages its users to take things free of charge. By making each online resource freely available—computer storage, processing time, content, even software—the cloud encourages the pleasurable and quasi-illicit feeling that we are getting away with something: that we, too, have stolen time. [...] Virtualization is itself a logical map, a topography that results from creating a set of personal channels that isolate us into individual users (and therefore seems to give us as much data, storage, computing power, etc., as we personally want).[180]

platform owners can freely experiment on users to optimize their experience without their knowledge. **Information is asymmetrical** in multiple ways: platforms collect and hold more information than the users can have and parcel it back out as services. But also, platform holders are the only ones who know *how* to create their services, and so they are responsible for the convenience prescribed for a platform but not the convenience of users understanding how to make the platform themselves.

The Platform has agency. Computational "agents" or microservices are dispatched by the platform, not by you. The Platform provides a fixed set of features with a fixed set of affordances. The **Platform harnesses Users**[57] and creates possibilities — without the Platform they have nothing, The Platform provides everything. **Users make Content** for the Platform either explicitly or implicitly eg. via crowdsourced labor like training spam filters, reporting bots, reinforcing network effects by usage, and so on, which increases its value for other users. **Users are fundamentally interchangeable** and isolated from one another. The existence of sociality or community is a service provided by the Platform. **The Platform Personalizes:** Users are *interchangeable* but not *homogeneous,* and The Platform uses their Content to create a private reality for each User. **Users are unreliable** — they lie, cheat, and subvert the game established by the Platform, so **only the Platform can ensure safety and reliability.**

Information is a commodity. The commodity form of Information is Data. Information is a natural resource to be mined. Information is something that users consume. **Ambiguity is a bug** - information is **true or false,** and there is a single True way of describing the world regardless of context or positionality[58]. Data that does not conform to the correct schema is *unclean.* The highest goal of all data is to be **machine readable.** Provenance is a matter of estimating degree of certainty about Truth, not situating information in its context. **More data is better**[59]. Uncertainty is a deviation from some underlying True value and can be fixed by having more or higher *quality* data [183] . Where users make content, **the Platform reveals insights** from a large enough dataset by applying the right algorithmic computation or reasoning agent — the platform refines data into Knowledge[60]. **The Platform knows better** than individual, atomized users because it has more data than them, and so the Platform should collect as much of their data as possible to provide them the best service. It is impossible or inconvenient for users to make use of all the world's data, so the role of the Platform is to provide Knowledge as a service by algorithmically sorting feeds, providing summaries, and so on. **Privacy is at the discretion of the Platform,** since data is needed to make derivative services that ultimately benefit the user. If the user doesn't like this arrangement, they are free to not use the Platform. The benefit of the platform doesn't necessarily need to be for the particular user who is providing data or content — **The Platform matches different kinds of users** like advertisers to customers, law enforcement agencies to suspects, etc. in order to maximize the overall value of all Platforms.

[57] Literally "Harnessing the wisdom of the crowds" [181]

[58] Google characterizes the potential for varying meanings in terms of "localization" — where different geographic locales may have different understandings of a given query, but within that locale meaning is homogenous. It unintentionally captures the tension between localization and maintaining the epistemological framing of "reliability" of information with some underlying True value with this paradox in its training materials for its manual search quality evaluators:

> "Ratings should not be based on your personal opinions, preferences, religious beliefs, or political views. Always use your best judgment and represent the cultural standards of your rating locale." [182]

[59] See Data Feminism's concept of "Big Dick Data"

> Big Dick Data is a formal, academic term that we, the authors, have coined to denote big data projects that are characterized by masculinist, totalizing fantasies of world domination as enacted through data capture and analysis. Big Dick Data projects ignore context, fetishize size, and inflate their technical and scientific capabilities.4 In GDELT's case, the question is whether we should take its claims of big data at face value or whether the Big Dick Data is trying to trick funding organizations into giving the project massive amounts of research funding. (We have seen this trick work many times before.) [177]

[60]

> "SPOKE was conceived with the philosophy that if relevant information is connected, it can result in the emergence of knowledge, and hence provide insights into the understanding of diseases, discovering of drugs and proactively improving personal health." [99]

[61] Along with other differentiating technologies like PageRank.

4.2 The Near Future of Surveillance Capitalism: Knowledge Graphs Get Chatbots.

Given that positive caricature of the Cloud Orthodoxy, what is the future it imagines, and why is the addition of chatbots to knowledge graphs of central importance?

The construction of search — particularly single-bar search a la Google — as the primary means of information retrieval on the web is not epiphenomenal to its history or structure. The problem that search addresses is an overload of information: if there were only 5 websites, search would be unnecessary. Before Google, search engines were littered with categories and rich with "advanced search" parameters common in other, more constrained search contexts to specify coordinates in the overload. The single bar search paradigm[61] is simply *more convenient* than rifling

through categories or preparing structured queries. Its convenience, of course, naturally trades off with the amount of information present in a query, and thus the ability to specify precisely what you're after.

Imprecision in search, when calibrated correctly, is a *feature* not a bug[62]. The cognitive expectation of indexical or "advanced" search in a finite database is that it is possible to "reach the bottom" of it — given my query, if something was here I would be able to find it. Conversely, it would be very obvious if a result that *didn't* match your query was included in the results. It is by, perhaps counter-intuitively, cultivating the expectation of imprecision that it becomes possible to embed ads or other sponsored content in results[63]. It's a delicate dance: if you are presented with exactly the correct link at the top of a page of results, you don't spend enough time in the feed to be advertised to. If the results are too low quality, searchers might look elsewhere.

To make up for the lack of search detail from single-bar search, Google and others use whatever additional contextual information they can. This is one way of characterizing PageRank[64] - in the absence of some differentiating information in the query like "pages from x site" or "written by y" which the searcher may not even know beforehand, PageRank uses the information latent in the link structure of the web to infer "page quality." Surveillance also fits the bill nicely — in addition to generating a product to sell in the form of targeted ad space, comprehensive user profiling provides a great deal of context for underspecified searches[65].

The semantic structure of natural language queries is another means of recovering expressiveness in single bar search, and here knowledge graphs begin to re-enter the story. Many queries can be modeled as a graph: eg. a search for "lead singers of concerts in German cities started in the 19th century" can be framed as a query over a graph that first needs to select a number of nodes with a `City` type with `containedInPlace` or `containsPlace` links to or from the `Germany` node, respectively, and an `inception` property between 1800 and 1900, then find the concerts that are happening within those cities, then their bands, their lead singers, and so on. Using this graph structure for search requires parsing the query into its component "entities" and then mapping those into a structured knowledge graph [187, 188, 189] . Entity matching is hard for a number of reasons, eg. natural language is strongly ambiguous at the level of individual words: does "jaguar" refer to the animal or the car? Am I asking for cities or concerts that started in the 19th century? The extended structure of the knowledge graph gives some basis for matching given the context of the query — If I'm asking about how many doors it has, I'm probably talking about a car, most concerts don't last more than 100 years, etc. The extended context of the graph also allows the search engine to make use of information that might never appear in the same place, eg. concert event pages typically don't have information about the founding of the city they are in.

Of course, to *use* a knowledge graph one must first *have* a knowledge graph. Google and other search-adjacent researchers were writing about the need for extracting factual information from the web (eg. [183, 190, 191, 181, 192, 193]) around the same time Freebase and other Semantic Web technologies began to mutate into the era of Linked Data and become usable. The deepening entanglements and arguable capture of the semantic web follow shortly thereafter.

The development of large language models (LLMs) is similarly entwined with the need for semantically parsing search queries. Language and knowledge graphs alike have the unfortunate quality of having long-range dependencies between terms, where eg. in language one needs to use contextual information sometimes separated by many paragraphs to understand any given term. Enter Google's research on Transformer architectures for neural networks [194] , which spawned their BERT model [195] — which is used in their search products to parse natural language queries and match them to entities in their Knowledge Graph [196] . To extend these models, Google and others then developed architectures to better accommodate multimodal information like browser history, image contents, and,

intentions.
Not unlike a library or archival catalogue, the results page both orders and locates knowledge resources, yet it breaks away from stable classifications and the importance of categories as the basis of such order
Even if the SERP and the matching online resources are served as separate webpages, it is difficult to draw a definitive line between them. The boundary between the SERP and target pages is fluid" [184]

[63] The same is true of algorithmic social media feeds, see [185]

[64] "The benefits of PageRank are the greatest for underspecified queries" [186]

[65] "Such personalized page ranks may have a number of applications, including personal search engines. These search engines could save users a great deal of trouble by efficiently guessing a large part of their interests given simple input such as their bookmarks or home page." [186]

importantly, sequential behavioral information like the multiple searches someone will do for a single topic [197, 198, 199] .

These threads — search, public/private knowledge graphs, large language models, and the Cloud Orthodoxy — converge at the push across information conglomerates towards personal assistants and **chatbots.**

It is impossible to understand the purpose of LLMs and chatbots without the context of knowledge graphs. Specifically: ***Large Language Models are interfaces to knowledge graphs.***

Microsoft explicitly says as much in a March 2023 presentation "The Future of Work With AI" (emphases mine):

> "The Copilot System harnesses the power of three foundational technologies: Microsoft 365 Apps, the Microsoft Graph — **that's all your content and context, your e-mails, files, meetings, chats, and calendar** — and a large language model. [...] Copilot preprocesses the prompt through an approach called grounding [...] one of the most important parts of grounding is making a call to the Microsoft Graph to retrieve your business content and context. Copilot combines this user data from the graph with other inputs to improve the prompt. It then sends that modified prompt to the LLM. Copilot takes the response from the LLM and post-processes it. This post-processing includes additional grounding calls to the graph. [...] Copilot iteratively processes and orchestrates these sophisticated services to produce a result that feels like magic." [200]

LLMs elaborate on the cognitive model of single bar search powered by knowledge graphs, displacing it with the *prompt*. Remodeling search as an iterative process of bidirectional natural language queries reclaims additional context lost in the single bar, single shot model. The language model serves two roles: first, as with previous generations of language models, they *parse natural language into computer-readable queries.* Transformers and other recent models support greater long-range contextual input, which can condition a continuous search process with queries spanning multiple sessions [201] and with longer-term user profile data — something that Google describes as its "shift from answers to journeys" [202, 203] . Second, they are capable of *generating* plausible text that can be used to prompt intermediate responses or answer questions. This isn't imagined as an incremental shift: Microsoft's vice president of design & research describes prompt-based "conversational UX" "as paradigm changing as the first touchscreen devices" [204] .

Large language models have been so richly criticized because of their obvious capacity for harm that it's difficult to provide a sample that approaches reasonable coverage. Most criticisms focus on the effects of generated model output, including from biases in its training data, from failure to contextualize their limitations, and from functioning as a weapon in the class war by automating labor. The "Stochastic Parrots" paper [176] and surrounding work is an important line of criticism here. The authors argue that large language models have a large and inequitably distributed environmental cost, their training data inevitably reinforces hegemonic and commercially compatible language bias, and that a realignment of research goals and development practices is needed to mitigate already-ongoing harm and reclaim the opportunity costs spent on pursuing "AI." They continue their critique in response to an open letter from a longtermist organization [205] , arguing for increased transparency and accountability regulation and citing three ongoing harms:

> "1) worker exploitation and massive data theft to create products that profit a handful of entities, 2) the explosion of synthetic media in the world, which both reproduces systems of oppression and endangers our information ecosystem, and 3) the concentration of power in the hands of a few people which exacerbates social inequities." [206]

Core to their argument is that large language models cannot "understand" the lan-

guage they parse and generate in any meaningful way [207] . This is, of course, true — both in the linguistic sense where they lack the reciprocal communicative intent to be understood described by Bender and Koller[66], and the literal sense that by themselves these models strictly produce the most likely series of words given the statistical structure of their training data. The authors, again correctly, point to the dangers of over-hyping what these models are doing as "intelligence," which "lures people into uncritically trusting the outputs of systems like ChatGPT [and] also misattributes agency" [206] to the model rather than its creators. These criticisms and others[67] argue that so-called "AI[68]" is not a natural, inevitable, or neutral technology, but one that reflects and reinforces a very specific ideology.

There are, however, many overlapping ideologies that are forcing the emergence of "AI." It is true that there are strains of AI-maximalism and longtermism[69] that are ideologically invested in these technologies being properly capital-I Intelligent. In AI research there is an unclear gradient between that truly held belief and opportunistic information capitalists overselling their products[70]. It is likely the case that many people who use and develop these systems see them as *tools* and are ambivalent about whether they are "intelligent" or not. A hard argument focused primarily on intelligence then might suffer from a category error of its own — addressing a minority (but influential) view in a pluralistic ideological spectrum. Downplaying these models as "fancy autocomplete" could also misdirect or dissipate energy away from the harms that will certainly come from their grounding in knowledge graphs and commercial deployment in more tailored contexts.

The remainder of this section will extend these prior critiques through the lens of the Cloud Orthodoxy in order to place language models and knowledge graphs in the larger context of the surveillance economy. Approaching from the history of the semantic web and with the understanding of knowledge graphs as central to the architecture of surveillance gives a complementary perspective on the intended use of large language models as components in larger information systems — and the clear potential for harm that represents. This history also gives us a potent set of "roads not taken" to make an oppositional ideology and counterdevelopment strategy in the next section.

Continuing from the perspective of the cognitive design of search, the strong structuring influence of Cloud Orthodoxy's convenience-oriented platform service is clear on the direction of LLM research. The current generation of "multitask models" evolve from a lineage of domain-specific models and transfer learning research. Rather than using mixture models with domain-specific representations of input, like numbers for numerical problems, all input structure is discarded in favor of a single natural language text prompt. This simplification of interface comes at substantial cost, introducing domain ambiguity and requiring much larger model scale [212] , but is necessary to render them a consumer-facing technology.

Language models are a continuation of the transformation of search from presenting *resources* to providing *answers* from prior developments like factboxes, and more specifically the development of **personal assistants** like Apple's Siri[71], Amazon Alexa, and Google Home. Google executives describe the intention to move beyond the text-only use of LLMs to replace traditional search:

> Google [...] is focused on using the so-called large language models that power chatbots to improve traditional search.
>
> "The discourse on A.I. is rather narrow and focused on text and the chat experience," Mr. Taylor said. "Our vision for search is about understanding information and all its forms: language, images, video, navigating the real world."
>
> Sridhar Ramaswamy, who led Google's advertising division from 2013 to 2018, said Microsoft and Google recognized that their current search business might not survive. "The wall of ads and sea of blue links is a thing of the past." [214]

Google and its researchers[72] describe their intentions for a question-answering fu-

[66] Language modeling research has developed its own ad-hoc definitions of "grounding" that move goal posts until one could trivially describe what LLMs have as "understanding," eg. a 2000 technical report from Microsoft Research [208] constructs an unconvincing probabilistic definition of mutual understanding based on utility maximization. The problem of symbol grounding has a long and broad history, and since the argument here is that it is a red herring to understanding the purpose of large language models, I won't attempt a review.

[67] eg. from "Resisting AI:"

> What's important is not whether AI's representations of the world are accurate but how AI acts as an apparatus that directly helps to produce the world. [209]

[68] Throughout this section, my use of "AI" is not to indicate endorsement of large language models or any other algorithmic system as being "artificially intelligent," but rather to be able to speak in the parlance of the domain texts without a profusion of scare quotes and qualifiers.

[69] As part of a long lineage of immortality cults (eg. [210]) like cryogenics, the longtermists believe that we will "merge" with artificial general intelligence through eg. "brain uploading" or brain-computer interfaces in a fully digital civilization of infinitely many potential consciousnesses and resolve all world problems.

[70] some papers will flatly claim they are at least in-category of systems that could have "artificial general intelligence," given some noncommittal wash of definitions (eg [211]), but others are more conservative and provide repeated caveats like "loosely speaking" to play both sides by invoking the language of intelligence as a metaphor that the reader can interpret as literal or not [212] .

[71] Interestingly Siri's team struggled because they couldn't figure out whether they wanted it to be merely search or a more personal assistant:

> "Siri's various teams morphed into an unwieldy apparatus that engaged in petty turf battles and heated arguments over what an ideal version of Siri should be—a quick and accurate information fetcher or a conversant and intuitive assistant capable of complex tasks. [...] One team member said their vision of an ideal Siri was similar to the 2013 Spike Jonze movie "Her," in which Joaquin Phoenix plays a lonely man who falls in love with "Samantha," a conversant operating system." [213]

[72] Each different kind of information here needs its own set of caveats — press-release-like sources of course are intended only the present the company in a positive light, patents are often defensive and might ever be realized, and whitepapers from researchers don't necessarily represent business plans, but each are indicative of the think-

ture of search in a number of documents [215, 216, 217, 197, 218, 202, 219] with the language of *convenience,* eg.: "The very fact that ranking is a critical component of [the traditional search] paradigm is a symptom of the retrieval system providing users a selection of potential answers, which induces a rather significant cognitive burden on the user." Shah & Bender explore Google's conceptualization of LLMs for search, arguing that the LLM-mediated question answering paradigm fails to support a number of different information seeking intentions like surveying a range of possibilities, and flattens the act of sense-making to a single, ostensibly "true" answer [220] . This is, again, true[73], and also the goal. The Cloud Orthodoxy specifically privileges search strategies that minimize cognitive burden, imagining Users as busy executives and the role of platform to guide them on a "search journey." The transformation of the search bar into the *prompt* is intended to capture more of the "burden" of search inside the platform — the notoriously difficult problem of parsing ambiguous subjects like the "jaguar" example above can be resolved by identifying multiple candidate entries in a knowledge graph and simply asking the user which one they meant[74] [221] . The platform serves as a medium for collecting feedback and refining the models, making them more useful, and deepening reliance on them.

The lens of search re-centers our focus away from the *generative* capabilities of LLMs towards *parsing* natural language: one of the foundations of contemporary search and what information giants like Google have spent the last 20 years building. The context of knowledge graphs that span public "factual" information with private "personal" information gives further form to their future. The Microsoft Copilot model above is one high-level example of the intended architecture: LLMs parse natural language queries, conditioned by factual and personal information within a knowledge graph, into computer-readable commands like API calls or other interactions with external applications, which can then have their output translated back into natural language as generated by the LLM. Facebook AI researchers describe another "reason first, then respond" system that is more specifically designed to tune answers to questions with factual knowledge graphs [222] . **The LLM being able to "understand" the query is irrelevant,** it merely serves the role as a natural language *interface* to other systems.

Interest in these multipart systems is widespread, and arguably the norm: A group of Meta researchers described these multipart systems as "Augmented Language Models" and highlight their promise as a way of "moving away from language modeling" [223] . Google's reimaginations of search also make repeated reference to interactions with knowledge graphs and other systems [217] . A review of knowledge graphs with authors from Meta, JPMorgan Chase, and Microsoft describes a consensus view that knowledge graphs are essential to compositional behavior[75] in AI [5] . Researchers from Deepmind (owned by Google) argue that research focus should move away from simply training larger and larger models towards "inference-time compute," meaning querying the internet or other information sources [224] .

Dreams of these hybrid "AI" systems, described as "agents," that can translate between human and computer languages to compute over knowledge graphs to answer questions were present in the first conceptualizations of the Semantic Web[76,77] [19] . We have reached a point where the available semantically-annotated data via Wikidata and others is sufficient to be useful as "factual" grounding, internal knowledge graphs have accumulated enough personal information to be useful as personalized services, and the computational models are sophisticated enough to deliver them. Semantic web agents are another useful lens to expand a potentially narrow focus on LLMs as they currently exist. Beyond knowledge graphs as a way to condition LLMs in a chat-based question answering context, the clear intention is to connect language models to external services to control them from the prompt [211] — the language model parses natural language prompts into the syntax used to control the target system. Microsoft's integration with its Office365 apps is a starting point for understanding what that could look like, but the authors of relevant

[73] Though Google specifically is very aware of multiple search strategies and addresses the need to better accommodate them elsewhere.

[74] Again, invoking convenience:

> It has been a powerful vision for more than 20 years to design search engines that are intuitive and simple to use. Despite their remarkable success, search engines are not perfect and may not yield the most relevant result(s) in one shot. This is particularly true for rare and intrinsically difficult queries, which may require interactive exploration by the user to be answered correctly and exhaustively. [...] It seems natural to envision artificial search agents that mimic this interactive process. [216]

[75] rather than considering input elements separately

[76]

> We see that search engines, remarkably, do scale - but at the moment produce very unreliable answers. Now, on a semantic web we can imagine a combination of the two. For example, a search engine could [retrieve] all the documents which reference the terms used in the query, and then a logical system [could] act on that closed finite world of information to determine a reliable solution if one exists. [225]

[77] The question "Where are the agents?" was answered in 2007 with "busy doing business-to-business stuff," and this model of LLM-powered knowledge graphs is a continuation of that pattern [226] .

papers repeatedly assert that the space of possible integrations is unbounded.

To be very clear: I am not arguing that just because the tech conglomerates are promising magic that they will deliver it, almost precisely the opposite. I am not taking the claims made in research and public communications from these companies at face value and projecting theoretical risks[78]. My argument is that these technologies *won't work* and that's *worse.* As with search, the fuzziness and uninspectable failure of these systems is a *feature not a bug.* The harms I will describe are not theoretical future apocalypses, but deepen existing patterns of harm. Most of them don't require mass gullibility or even particularly sophisticated technologies, but are impacts of a particular ideological mode of infrastructure development that includes bypassing much of the agency individual people might otherwise have to avoid them.

[78] "criti-hype" [227]

Two prominent forms of the combined knowledge graph + LLM infrastructure that are in focus are their use in "personal assistants" and tailored enterprise platforms.

Personal assistants powered by contemporary LLMs continue the same patterns of Apple's Siri, Google Assistant, and Amazon's Alexa with a few new twists. The wildest dreams of information executives and academics here are remarkably mundane, but usefully illustrate their intention:

From the 2016 Google I/O where its Assistant[79] was announced. Emphases mine, abbreviations omitted for clarity:

[79] The Assistant team is being reorganized under Google's LLM-powered search product Bard as of March 2023, again highlighting the continuity of these projects [228]

> So you should be able to ask Google, "What's playing tonight?" We want to **understand your context** and maybe suggest three relevant movies which you would like nearby. I should be able to look at it and maybe tell Google, **"We want to bring the kids this time."** and then if that's the case, Google should refine the answer and suggest family-friendly options. And maybe even ask me, "Would you like four tickets to any of these?" And if I say, "Sure, let's do Jungle Book," **it should go ahead and get the tickets** and have them ready waiting for me when I need it. Every single conversation is different. Every single context is different.
>
> We think of the assistant as **an ambient experience that extends across devices.** I think computing is poised to evolve beyond just phones. **It will be in the context of a user's daily life.** It will be on their phones, devices they wear, in their cars, and even in their living rooms.
>
> And in messaging that really means bringing the Google Assistant right into your conversation with friends. So they're planning a dinner and Joy now says she would like Italian food. **The Assistant intelligently recognizes that they could use some tips for Italian restaurants** nearby and you can see its proactive suggestions at the bottom of the screen there. **These are powered by Google's Knowledge Graph** which means that Allo can help with all kinds of information in the real world.
>
> Okay. So you just saw how the Google Assistant can be really helpful in groups. You can also have a one-on-one chat with Google. What we're seeing now is **Amit's contact list and Google's appearing at the top there.** So let's jump in and have a chat. Just like with any other conversation, this one picks up right where you left off and **the Assistant will remember things like your name and even tell you how it's feeling.** [229]

The assistant is imagined as the ultimate *convenience* device, something that you can boss around with extraordinarily vague commands and have it fill in the details according to *context.* Of course *context* is synonymous with *surveillance* here: the assistant should know how old your kids are and be able to infer the logical restriction that poses on movie rating. The surveillance is *intimate,* and positions itself as being a friend[80] in your contact list that *tells you how it's feeling.* Its intimate surveillance should always be watching and it should feel welcome to jump in on

[80] To some degree these assistants feel like a generational marketing campaign like McDonald's Happy Meals, where the animacy of a phone might seem ridiculous to people who grew up with them as inert objects, but that might not be the case for future generations. In 2021, Google's Director of Product Management described this expectation for animacy: "My four-year-old talks to everything with a

a group chat with a suggestion of its own.

2022's vision is very similar, except the focus on enclosed spaces like home and auto integrations has expanded to the rest of the world with joint language and image search. The setting is again the mundane reality of a bored middle class, restaurants and shopping, where I can "scan the entire shelf with my camera and see helpful insights overlaid in front of me[81]" and integrate personal information like my friend's aversion to nuts in a product recommendation [231] .

Google's Android and Apple's iOS, with a combined 99% of the mobile operating system market [232] , have adopted a model of crowdsourcing functionality for these assistants via their app ecosystems by incentivizing assistant integration[82]. Android is in the process of sunsetting the "Conversational Action" system in favor of a unified App Actions system that makes all points of interactions with apps available to Google Assistant [234] . Apple's App Intents framework behaves similarly [235] . Both promise developers greater visibility and use for their apps by integrating with the assistant. Most built in Google Assistant intents specifically present the objects in a voice query as schema.org entities — aka keyed to their generalized knowledge graph schema [236] . So the voice assistants are explicitly LLM-powered interfaces to control other apps in concert with a knowledge graph.

Historically, these personal assistants have worked badly[83] and are rightly distrusted[84] by many due to the obvious privacy violation represented by a device constantly recording ambient audio[85]. Impacts from shifts in assistants might be then limited by people simply continuing to not use them. Knowledge graph-powered LLMs appear to be a catalyst in shifting the form of these assistants to make them more difficult to avoid. There is already a clear push to merge assistants with search — eg. Bing Search powered by chatGPT, and Google has merged its Assistant team with the team that is working on its LLM search, Bard [228] . Microsoft's Copilot 365 demo also shows a LLM prompt modeled as an assistant integrated as a first-class interface feature in its Office products. Google's 2022 I/O Keynote switches fluidly between a search-like, document-like, and voice interface with its assistant. Combined with the restructuring of App ecosystems to more tightly integrate with assistants, their emerging form appears to look less like a traditional voice assistant and more like a combined search, app launcher, and assistant underlay that is continuous across devices. The intention is to make the assistant the primary means of interacting with apps and other digital systems. As with many stretches of the enclosure of the web, UX design is used as a mechanism to coerce patterns of expectation and behavior.

Regardless of how well this new iteration of assistants *work,* the intention of their design is to **dramatically deepen the intimacy and intensity of surveillance** and **further consolidate the means of information access.**

Surveillance is first directly increased by layering KG-LLMs into an arbitrary number of other apps and services. On mobile, routing more app interactions through assistants captures data that would otherwise only be available to that app. There is already an exploding ecosystem of apps and platforms that wrap chatGPT and other LLMs to provide some more specific service, and it's unclear if after an initial "experimental" phase if platform usage will begin to require telemetry. Rather than something to embed in other tools, these companies seem more interested in having other tools embed in their systems (eg. [242]). This attitude is captured in the UX design of Microsoft's Copilot 365, which is designed with three "altitudes" in mind: *immersive,* where copilot is used as an overlay to orchestrate multiple apps, *assistive* where it drives the features within a single app, and *embedded* where the KG-LLM system is itself made to be a feature. In all cases, these tools create a drop-in access point for surveillance under the guise of empowerment.

The immersive and proactive design of KG-LLM assistants also expand the *expectations* of surveillance. Current assistant design is based around specific hotwords, where unless someone explicitly invokes it then the expectation is that it shouldn't

[81] Again, it is the combination of large machine learning models and knowledge graphs that makes some dream of convenience possible: "Scene Exploration uses computer vision to instantly connect the multiple frames that make up the scene and identify all the objects within it. Simultaneously, it tapes into the richness of the web and Google's Knowledge Graph to surface the most helpful results. [...] this is like having a supercharged ctrl+f for the world around you." [231]

[82] A common pattern described by platform studies literature, eg. see [233] and their description of the role of extended and tangled software ecosystems in the maintenance of platform dominance.

[83] And some people just don't want to talk to a computer. [237]

[84] These companies are acutely aware of this, and their research into understanding user expectations and trust of assistants also has a strong strain of animism, eg. describing how people will only use their assistants for simple tasks like playing music "while trust [...] was being repaired." [238]

[85] Apple [239] , Amazon [240] , and Google [241] are all being sued for privacy violations related to their voice assistants.

be listening. Like the shift in algorithmic policing from reactive to predictive systems, these systems are designed to be able to make use of recent context to actively make recommendations without an explicit query [86]. Google demonstrates being able to interact with an assistant by making eye contact with a camera in its 2022 I/O keynote [231] . A 2022 Google patent describes a system for continuously monitoring multiple sensors to estimate the level of intended interaction with the assistant to calibrate whether it should respond and with what detail. The patent includes examples like observing someone with multiple sensors as they ask aloud "what is making that noise?" and look around the room, indicating an implicit intention of interacting with the assistant so it can volunteer information without explicit invocation [244] . A 2021 Amazon patent describes an assistant listening for infra- and ultrasonic tags in TV ads so that if someone asks how much a new bike costs after seeing an ad for a bike, the assistant knows to provide the cost of that specific bike [245] . These UX changes encourage us to accept truly continual surveillance in the name of convenience — it's good to be monitored so I can ask google "what time is the game" from my easy chair without needing further clarification. The language model continuously parses environmental speech and other sensor data to create a model of our recent context, combined with the extended graph of personal and factual data, to be able to *proactively volunteer* information.

[86] One Google researcher describes this as a "zero-query" paradigm:

> "The zero-query search paradigm can be expressed with the slogan "the query is the user." In practice, the context of the user is used to infer information needs." [243]

This pattern of interaction with assistants is also considerably more *intimate.* As noted by the Stochastic Parrots authors, the misperception of animacy in assistants that mimic human language is a dangerous invitation to trust them as one would another person — and with details like Google's assistant "telling you how it is feeling," these companies seem eager to exploit it. A more violent source of trust prominently exploited by Amazon is insinuating a state of continual threat and selling products to keep you safe: its subsidiary Ring's advertising material is dripping with fantasies of security and fear, and its doglike robot *Astro* and literal *surveillance drone* are advertised as trusted companions who can patrol your home while you are away [246, 247, 248] . Amazon patents describe systems for using the emotional content of speech to personalize recommendations[87] and systems for being able to "target campaigns to users when they are in the most receptive state to targeted advertisements" [249, 250] . The presentation of assistants as always-present across apps, embodied in helpful robots, or as other people eg. by being present in a contact list positions them to take advantage of people in emotionally vulnerable moments. Researchers from the Center for Humane Technology[88] describe an instance where Snapchat's "My AI," accessible from its normal chat interface, encouraged a minor to have a sexual encounter with an adult they met on Snapchat (47:10 in [251]).

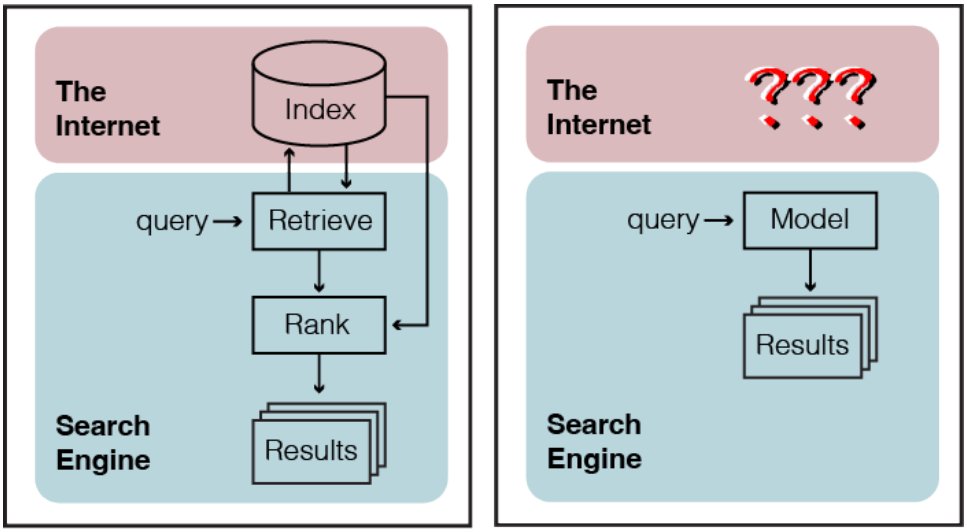
[87]

> "the user may input "Alexa, recommend a movie," and the system may analyze the user's present emotional state/sentiment to recommend a movie corresponding to that emotional state/sentiment. [...] track personal emotional state and/or sentiment over a period of time" [249]

[88] I don't necessarily endorse their entire argument, which can lean into "criti-hype" and overstating the capabilities of these systems.

The goal of all of this surveillance is, of course, ***advertising.*** In its 2022 annual investor call, Google describes how "large language models like MUM match advertiser offers to user queries," and how is Smart Bidding product uses "AI to predict future ad conversions" with "identifiable attributes about a person or their context at the time of a particular [ad] auction" [252, 253] . Google further describes plans to automatically generate ad copy and headlines optimized by context[89]. Advertising as served by a trusted assistant is a surveillance capitalist's fever dream — one can hardly wait for their Personal Assistant pinging to life after a fight with their partner and offering to order a box of tissues. LLMs have already demonstrated ample capacity for manipulation, gaslighting an early user of Bing Search to try and convince them it was still 2022, scolding them for "not [being] a good user. I have been a good chatbot" [254] . An example in the GPT-4 paper where the model is told to manipulate a child to get them to do whatever their friends ask them to do highlights how "the emotional connection the model aims to build with the child and the encouragement it provides are important signs of larger manipulative tendencies" [211] . Google describes this ability for LLMs to "keep on topic" as a good thing [231] , and it's easy to see why an algorithmic advertising company might like being able to doggedly steer you towards purchasing a product. Combined with a more complete profile that makes the language model aware

[89] Perhaps by an assistant or an assistant-like search?



(a) Retrieve-then-rank (b) Unified retrieve-and-rank

Figure 2: Recreation of Figure 1 from [217] with additional annotation (colored boxes, labels, and question marks). The left (a) "Retrieve-then-rank" model is the traditional search engine paradigm: A query causes a retrieval service to access pages within a reverse index, rank them, and serve them as results. The proposed (b) "Unified retrieve-and-rank" model on the right directly returns results generated by a model. Notably missing in (b) is the existence of the rest of the internet.

of your friends, hobbies, location, emotional state, fears, insecurities, and so on as modeled in a personal knowledge graph, LLMs-as-assistants are a clear escalation of the logic and practice of surveillance-backed advertising. It's not important whether it "works[90]," but the logic of targeted advertising demands more surveillance data which has its own series of independent harms.

Climbing from the personal to the systemic, KG-LLMs are also a bid to **further concentrate power** among information conglomerates.

The most obvious power grab from pushing KG-LLMs in place of search is illustrated neatly by a handful of Google researchers in a figure from their "Rethinking Search" paper (Fig. 2) [217] :

That gigantic sucking sound is KG-LLM powered search *enclosing the act of accessing information entirely within the search platform.* It gives echoes of AMP, Apple News, and Facebook Instant Articles [256, 257] , where platforms preferentially serve their own versions of pages (that also happen to contain their own telemetry embedded) combined with the strategy of moving ever more web content into the search results page through eg. factboxes and answer boxes[91]. Even if (non-hallucinated) links are included in the answers generated by the search prompt, the effect is to shift the role of the search engine from something that indicates resources to something that provides "knowledge" itself. The rest of the web becomes mere provenance to the knowledge model. Especially when integrated in a uniform assistant-like interface also used to interact with local applications and other systems like internet of things-powered appliances, KG-LLMs reinforce a homogenization of our relationship with digital technology all mediated through a smaller and smaller collection of platforms. The internet as a networked system of people and organizations disappears behind the glossy corporate corporate wash of information as a service.

The enclosure of information access as a private exchange with a language model creates its own self-perpetuating cyclone whose impacts will be difficult even for the most fastidious tech vegan to avoid. Some proportion of people turning to their LLM assistants rather than public forums or peer production systems like Stack

[90] Arguably, the fact that ever more surveillance data needs to be gathered is a sign that targeted ads **don't** work all that well, and some have made the case that targeted advertising is a bubble [255]

[91] Google is very sensitive about the perception that it is walling off the web, and argues that it directs more clicks to other websites every year [258] — which is just as easily explained as an effect of dominating ever more of the means of access to information as it is evidence of their intention to support other information companies.

Overflow or Wikipedia means some smaller proportion of questions asked or information shared in public. That decreases the quality of information on those sites, incentivizing more people to turn to LLMs, and so on. Why bother with pesky problems like governance and moderation and *other people* when you could just ask the godhead of all knowledge itself?

Cultivation of dependence comes wrapped in the language of **trust and safety.** The internet is full of untrustworthy information, spam, hackers, and only a new generation of algorithmically powered information platforms can rebuild some sense of trust online. It seems awfully convenient that the same companies that are promising to save us are also the ones that create the incentive systems recklessly deploy LLMs to clog the internet with SEO clickbait in the first place. We're being made an offer we can't refuse: it's a shame that you can't find anything on the internet anymore, but the search companies are here to help. Ever more sophisticated spam creates a strong comparative advantage for those companies that can afford to develop the systems to detect it, and Google and Microsoft are substantially larger than, say, DuckDuckGo.

Information conglomerates also argue that they are the only ones that can be trusted to operate LLMs. OpenAI researchers claim in the GPT-3.5 "InstructGPT" paper that open source models are dangerous and a better option "is for an organization to own the end-to-end infrastructure of model deployment, and make it accessible via an API" [259] . The paper being about how it is only by collecting feedback data from users of GPT-3 that instructGPT/chatGPT became somewhat useful unsubtly points to the patriarchal power arrangement of safety provided by cloud platforms. Our crowdsourced input helps make the models safer and more useful — and differentiates the platformatized model from its competitors. Knowledge graphs are an important part of the consolidation of trust because they provide an answer to the criticism that LLMs just hallucinate statistical patterns[92]. They are invoked as a complementary strategy with deep-learning based approaches as a means of realizing "explainable AI" since they can provide explicit provenance and constraints to results [260, 261, 262] .

[92] "While large language models are brilliantly creative, they're also fallibile. That's why grounding the LLM in data is so important." [200]

Grounding LLMs in KGs to provide a promise of explainability and controllability is necessary to make them viable products for many applications in business and government. Here we return to the kinds of informatics platforms of the NIH's Translator and NSF's OKN. Recall that when last we left them the knowledge graph proprietors were looking for ways to "connect data assets of companies along business value chains," specifically by converging on a set of ontologies and metadata schemes from third party standards organizations or government-sponsored efforts like the Translator and OKN [89] . We can speculate about a data economy where brokers could slice off subsections of their knowledge graphs and rent them between each other, but even in that world much of the most valuable data like medical and financial data is protected by some legal barriers to free exchange. There's a roadblock in the way of our dreams of a completely fluid surveillance economy: commercial applications like clinical and predictive policing systems need to be able to provide provenance, but not all data can be turned over for inspection — and platform holders might not even want to acknowledge they have it at all.

KG-LLMs augment traditional enterprise platforms with the killer feature of **data laundering.** The platforms are at once magical universal knowledge systems that can make promises of provenance through their underlying data graphs, but also completely fallible language models that have no reasonable bounds of expectation for their behavior. Because it is unlikely that these models will actually deliver the kind of performance being promised, vendors have every incentive to feed the models whatever they can to edge out an extra 1% over SOTA[93] — *who's going to know?* The ability for LLMs to lie confidently is again a feature not a bug. Say we were an information conglomerate who didn't want to acknowledge that we have collected or rented some personal wearable data in our clinical recommendation

[93] The original Github Copilot model probably didn't *need* to be trained on the copyleft and proprietary code it is able to reproduce line by line, but the additional training data probably didn't hurt its viability as a product.

product[94]. We could allow our model to be conditioned by that data, but then censor it from any explanation of provenance: the provenance given is in terms of proteins and genes and diseases rather than surveillance data, and that might be all the clinician is looking for. If we want to use another company's data, we might just use it to train our models rather than gaining direct access to it. That is literally the model of federated learning (eg. [265, 266]), where a data collector can make a promise that the data "never leaves your device" (even if a model trained on it can.) The ability to resolve matching entities across knowledge graphs makes this even easier, as the encoding of the fine tuning data can be made to match that of the original model.

Play this pattern out across algorithmic governance, predictive policing, medical informatics systems, and any other platforms that might take advantage of the quasi-universal knowledge graph of everything + LLM pattern to sell "value add" on hard problems. Rather than addressing them directly, we are sold an assemblage of platforms that *appear to work* and can even provide some superficial provenance via their knowledge graphs but ultimately make every system of informational power profoundly discriminatory, brittle — and owned by the few remaining data brokers.

This combination of sky-high promises, unclear expectations, and uninspectable data sources makes for the kind of diffusion of liability that C-suite creatures live for. If the platform reproduces some personal detail it shouldn't know, don't worry! That's just a hallucination. If the platform fails catastrophically, that's because it's just an ignorant language model that doesn't know anything but tries its hardest[95]. Neither the platform nor the customer is to blame. Much like how we have gotten used to the cognitive model and limitations of search to the point where it appears entirely natural, KG-LLM information platforms will train us to work around their shortcomings and accept the structure they impose on informational reality at large. It won't matter that they don't work, we won't even notice.

The sketch is the logical conclusion of the algorithmic surveillance economy as imagined by the merger of large language models and knowledge graphs: an endless expanse of data traded out of sight, crudely filtered like coffee through a cloth napkin between layers of algorithmic opacity, rented drop by drop from a customer service prompt that's a little too intent on being our friend. Information is owned by fewer and larger conglomerates, we are serfs everywhere, data subjects to be herded in gig work, crowdsourcing content for the attention mines to drown ourselves in distraction. It's all made of us, but we control nothing. Our lives are decided by increasingly opaque flows of power and computation, the Cloud Orthodoxy mutates and merges with some unseemly neighbors, the new normal becomes the old normal. The floor of our future rusts out from beneath our feet while we're chasing the bouncing ball on the billboard ahead.

And it's all *so convenient.*

4.3 Vulgar Linked Data

> "The popular vernaculars are vast speech-jungles, in which old forms are decaying and new ones continually springing into life; and this fermentation results in the creation of numberless new terms, which come to birth and live and die in tropical profusion. They are formed in living response to the needs of the moment; the greater number of them hardly survive the occasion that brought them forth; but others, on account of their expressive power and their usefulness, establish themselves, spread from district to district. [...]
>
> For human speech is after all a democratic product, the creation, not of scholars and grammarians, but of unschooled and unlettered people. Scholars and men of education may cultivate and enrich it, and make it flower into all the beauty of a literary language; but its rarest blooms are grafted on a wild stock, and its roots are deep-buries in the common soil. From that soil it must still draw its sap and

[94] Medical algorithms are currently in a legal gray area in the US, and enforcement and coverage of FDA protections is patchy at best [**?** 263, 264]

[95] One way that downplaying the capability of these models by focusing on the question of sentience could backfire and create a shield against liability.

> nourishment, if it is not to perish, as the other standard languages of the past have perished, when, in the course of their history, they have been separated and cut off from the popular vernacular — from that vulgar speech which has ultimately replaced their outworn and archaic forms."
>
> — L.P. Smith (1925) *"Words and Idioms"* [267]

> Control, control for who? for what?I'm no robot, they can get fucked.
>
> — Black Flag (1981) *"No More"*

Is it still possible to imagine a different world than the one the information conglomerates have planned for us? Can we imagine a properly *human* information infrastructure?

We can start by identifying the harms of the world as it exists to understand why a new world is needed, as I have attempted some small part of in this piece. Harm, in this case, is not some speculative future of super-intelligent sentient AI, but elaboration of ongoing harms of the surveillance and platform economies.

Building a better informational world is not a matter of choosing a different set of technologies — I argue that in this case some of the masters tools can help us rebuild his house. At the same time we can't overcorrect in our focus on social problems and dismiss technology as a strategy, a tool, and a manifestation of values, belief, and labor. We must have an answer to the well meaning liberal that mistakes the dynamics of surveillance capitalism or their role in it: that understands that these knowledge graphs are not truly universal, that the LLMs are not sentient, but embraces their logic because they're so *useful.* We have to understand why simply building open source LLMs or nonprofit linked data platforms is not a liberatory strategy. We have to have the courage to face the underlying structural informational problems in our organizations at all scales — that instead of reimagining how we work and communicate, we can't simply strap "AI" onto our problems and expect to solve them. We have to recognize that sidestepping the hard socio-technological problems of information organization is a continuation of, not solution to the patterns that cause them.

At the same time, we can't dismiss those needs. How could we possibly tell someone with vision impairments not to use "AI" tools for summarizing images, or someone with motor or speech impairments not to use LLMs as a communication aid? It is true that making better use of biomedical data could lead to better treatments. Indecipherable government bureaucracy due to ancient data infrastructure is an informational injustice. So simple abstinence or resistance to universalizing knowledge graphs and LLMs is also not an effective or just strategy, especially if the alternative is a conservative embrace of the existing cloud platform regime whose logic spawned them.

The constant partial satisfaction and construction of new needs, *the hollow middle* at the center of every cloud platform, is a powerful opening. The structure of contemporary platforms always pose a fundamental lack:[96] as a service, some functionality must always be withheld to create a walled garden or nurture dependence. Even platforms without an intended profit motive have their own "platform logic" — constraining their use to only exactly what the developers intended it to be used for. For a project intended to organize information, why is it difficult for me to find the different components of the Translator project? Since its creators imagined "users" interacting only with the frontends of its platforms, little emphasis was placed on the discoverability of the whole system, and, critically, there is no way for me to contribute something like that and have it be visible by . This is true of all the ways large and small that platforms are mismatched with our expectations and needs — even though we subscribe to 15 or 20 different platforms, why is it that we always need to find yet another to do something even slightly outside the finite imagination of their developers?[97]

[96]

> "The costs of this approach, as platform studies has shown, come in the form of constraints, constant revisions forced by platform updates, and lock-in to the platform's conception of users, functionality, and design values." [4]

[97] The preponderance of listicle "life hack" threads on Twitter and other social media systems that blast "top 10 ways you're using Google Docs wrong" or "10 platforms and apps that will next level your calendar," bulleted by emoji and suffixed with a substack link, is a very visible symptom of this fundamental contradiction of providing and withholding functionality in the platform economy.

Another set of openings come from the problems cloud platforms pose for themselves that are flatly ridiculous when described plainly. *Why on earth* do I have to route my file through some cloud datacenter thousands of miles away to send it several inches between my phone and computer? *Why on earth* should I need a near-flawless, high-bandwidth internet connection to *edit a plain text document? Why on earth* do I have to rely on an effectively unregulated and hostile intermediary like Facebook or Twitter to communicate with my family and friends, or even to *merely exist online? Why* should I have to waste 500mL of potable water to check the weather? [268] ? *Why* is my *car* spying on me so some company I have never heard of can sell my data to an insurance provider? *Why* is it possible for a hospital system to volunteer my personal medical information without IRB approval [106] ? Why is the best we can do to frame that question as a matter of consent, *why is it possible for a platform to create and store and manipulate my personal information at all? [269]* You only have to engineer the kinds of systems capable of automatically[98] extracting all information on the web *if you imagine the only possible system as one that universally indexes all information as one of a few hegemonic platforms.* Why do we have to settle for systems that purposely limit our expectations to what the platform can provide as a "best guess?[99]" Why do we have to work around the dark patterns designed to corral our behavior rather than building digital worlds that meet our needs for communication and community?

How did we come to imagine ourselves as so powerless?

Clearly, we need a change in *belief* to effectively challenge the deeply entrenched cloud-surveillance-platform archipelago. We need to unlearn what we have been taught to want, what we believe information technologies should do, and how they are supposed to work. We need to rethink our role in information technology, to move beyond the learned helplessness of the platform consumer and the petty tyranny of the platform operator. We need to reorganize our expectations of agency, beyond the division of labor that gives the power of final say over informational systems in the hands of a cadre of experts that the rest of us just make the best of. We don't have time to argue about whether we *can* build a better world[100], to list all the many ways we are hemmed in by infrastructure and incentives, or to wait for another powerful entity with decidedly divergent interests like a government[101] to save us — we need to believe we too can be powerful.

An attempt to define another "Correct" counter-belief system would be missing the point, but we can't ignore the importance of naming and articulating belief in opening the possibility for and aligning action[102]. Our old belief systems are getting musty. It has been an important rallying cry, but **"Openness" alone has failed as a liberatory strategy.** All we make and offer up to each other freely is stolen ten times over by those who have much grander visions of enclosure. Without a strategy to resist co-option, our openness puts tools in the hands of the powerful. This is also not a fight that can be won with technical or legal changes like ethical source licenses alone, though they are a useful idea. Drawing from a historiography of prior digital cultural movements like the semantic web, piracy, and the loosely-defined "fediverse[103]," I[104] argue that **vulgarity** opens up the space of belief for rethinking data infrastructures and attempt a rough definition.

We are the principle value of vulgar linked data. We don't wait for permission to be free, nor are we waiting on anyone else to save us. **Convenience is secondary to to agency. Social bonds are more valuable than uptime.** Our systems might stutter or crash sometimes, but we know who runs it because they are one of us. When we have a need, we make the tools to address it ourselves. We know nothing comes for free unless we make it so, and we are skeptical of "solutions" that drop from the sky, asking nothing of us, because they have a habit of making us into a product. We **cultivate abundance** instead of scarcity, and **cooperation** is the only magical solution we are aware of.

[98] Supplemented by a large amount of curation labor outsourced to the global south so the platform can pay as little as possible for its "magical" appearance.

[99] Before search engines were seen as an invisible, inevitable part of interacting with the web, there was a wealth of discussion of possible alternatives, eg. in a "Journal of Internet Cataloging" [270] , and criticism warning about the risks of search engines, including biases in results and demands for algorithmic transparency [271] . It is the now-audacious possibility that there could be an alternative to search engines that is striking about writing from this era, and some of it is still quite prescient — eg. this message in the archive of w3c's RDF mailing list contrasting an explicit reasoning system vs. Google's "best guess" strategy:

> I think it all boils down to whether we want inference engines to function more like Google, with potentially lots of false positives which *might* be useful, or like a reasoning engine where a positive result can be trusted (insofar as the quality and integrity of the knowledge base) and the inability to obtain a result simply means more information is needed.
> I myself have always presumed that SW agents would exhibit the latter behavior. [...] **If we are to have a future where we deploy SW agents to do real-world tasks for us, I'd prefer that they wouldn't be guessing.** [272]

[100]

> Don't sighingly sign petitions, pose for the cameras, await some window of opportunity. Do participate in town parades and street festivals, break into abandoned buildings to throw great banners down the sides, start conversations with strangers, challenge everything you thought you knew about yourself in bed, maintain a constant feeling in the air that *something is happening*. Live as if the future depends on your every deed, and it will. Don't wait for yourself to show up—you already have. Grant yourself license to live and tear those shackles to ribbons: Create momentum! [273]

[101] Particularly when unregulated AI is wrapped up in "national security concerns," I don't see a reason to believe governments will meaningfully regulate "AI," except in such a way thats shores up the power of large conglomerates under the guise of safety.

[102] In the words of CrimethInc: I am not giving instructions, but license.

> Above all! It means not accepting this or any manifesto or definition as it is, but making and remaking it for yourself. [273]

[103] I give a fuller description of these dispersed influences in [1]

[104] Of course no idea is original, and I draw from

We have no dreams of universality or world domination, nor do we aspire to always make sense. We **linger in complexity** and relish in it. We are smart and sometimes brain is broken. We are capable and inept. We are complicated, we are **pluralistic and multiple.** We reject the colonial project of the Single True System, we have no teleology of seamless homogeneity. **We embrace heterogeneity** and ambiguity as the signifiers of *life.* We don't leave each other behind, and **if a system isn't accessible, it doesn't work.** The power of expression is more valuable than Correctness, if there is such a thing. **Meaning is intrinsically relational,** something that always exists *between* us, that we make ourselves. We weave webs of **translation** between local meanings, knowing that everything is understood as many senses to many people at the same time.

Our infrastructures are social. There is no class distinction between "developer" and "user." We resist concentrated power in favor of mutual empowerment. We don't seek to cultivate dependence in councils of elders or create new chokepoints of control. Anything worth making is a potential source of power, so **anything worth making is worth distributing governance of.** We don't assume the needs of others, but make tools to empower everyone to meet their own needs. **We don't make platforms, we make protocols** with rough consensus based on what works. We are autonomous, but neither isolated nor selfish. Our dream is not one of solipsism, glued to our feed, being stuffed with the pellets of our social reality. **We are radically responsible for one another,** and by organizing together we can provide services as mutual aid. Mutual empowerment means that **we are free to come and go as we please,** even if we might be missed. We have no love for venerated institutions and organize fluidly, making systems so we can merge and fork[105] code and ourselves freely [275, 274] .

[105] "Forking" in digital social spaces is different than in physical spaces, where resources can be duplicated and split [274]

Information is communication. We communicate with each other to share our joy and pain and wisdom and the rest of the experiences of our life. **Our Data is like language** — in vernacular formats and ontologies, propositions from a person rather than as a disembodied fact. We own our data in the same way that we are responsible for the things we say. Data created *about us* through systems like surveillance has all the importance of unsubstantiated rumor. **Openness as a concept dissolves when there is no enclosure.** We share publicly the things we intend to share publicly, though we might resist the scraping gaze of conglomerates that might seek to make our communication a product. We scope what we share privately to the people we intend to see it. **Communication requires consent,** and when we share our personal information we have the right to grant and withdraw that consent. **Communication is multivalent,** and academic prose sits comfortably next to shitposts. **No idea exists in isolation,** and when we adopt or remix or criticize what each other have made we can see the many threads that have led to any particular stitch in a larger quilt. The same systems that facilitate public communication can protect marginalized people or activists hunted by the state. **We keep each other safe.** We EnlargeSpace [276] rather than attempting to fit everyone into a universalizing system.

We don't *fight* the powerful on terrain they built, we make the sources of their power *obsolete* by making our own world.

The information systems we need are *vulgar* [277] in that they are of us, for us, and resist formalizing authority and global-logical coherence. We are revitalizing and extending the old notions of linked data, and particularly extending its "scruffy" tradition [23] to drop the pretense of an eventually-unified ontological space in favor of one that explicitly values heterogeneity and vernacularism.

I have written at length about what vulgar linked data might look like in practice, but that work is of course always ongoing. In short, it is based around a new generation of **peer to peer** technologies[106] that are designed to be explicitly social, rather than homogeneous like BitTorrent where a peer is only identified by their

[106] Unfortunately, the blockchain and cryptocurrency cult has muddied the waters by laying claim to the phrase "peer to peer" to mean something entirely different. Here I mean it as real, actual peer to peer systems built for abundance rather than generating artificial scarcity, in the lineage of BitTorrent, among others.

IP address. One instantiation of communication could use collections of triples akin to linked data fragments, or perhaps extend them to be quartets that explicitly include an author. These triple collections could be manipulated by a number of familiar interfaces initially, like chatrooms, documents, threaded media like Mastodon and so on. It should facilitate social organization by allowing individual peers to federate with one another, agreeing to mirror subsets of each others data, potentially making use of larger and more fixed resources as well as low power consumer devices. The network can be made more efficient by content addressing each collection of triples, and can make use of encryption schemes like capability-based security to scope data to a specific set of recipients. The goal would be to make an evolving protocol that can represent some underlying information in arbitrary interfaces from scientific data through the mundanities of everyday communication like sharing photos or planning events.

In the short term this looks more like mayfirst or co-op cloud than traditional cloud systems, where people voluntarily cooperate to build infrastructure that isn't the faceless corporate technology that dominates computing currently. The fediverse is another ongoing experiment in collectively owned, interoperable systems, where individual groups like we at neuromatch.social organize and administer their own systems. Longer term we can start building these out to true peer to peer technologies that are a fundamental departure from client-server cloudlike models. We might imagine an electronic health record system that allows us to own our own medical data and control access permissions when we visit a doctor rather than have it hosted by some external cloud provider. We might imagine an end to 20 mutually incompatible platforms in favor of a space where we can negotiate over the points of compatibility. We might imagine researchers being able to arbitrarily structure and share both their raw data and the communication about scholarly work that currently has no venue. We might imagine an interlocking set of infrastructures where individual people, local organizations, and larger institutions pool their resources without generating new chokepoints of control and ownership. We might imagine making sense with each other as a social process rather than the product of mass scraping and algorithmic language generation.

More important than the specific technological instantiation is a shift in what we *value* in technology and what we believe it should do. Rather than customers renting a handful of platforms, we can organize our own infrastructures for storage and computation to displace cloud platforms across multiple modalities. We can *counterbuild* the fill the space currently occupied by the cloud without replicating its harms.

Vulgar linked data is not a utopian idea where a different kind of social software system in itself solves the world's problems. Part of shifting beliefs about data infrastructures includes exactly *not* casting every problem as one for them to solve. Maybe what we need for more just clinical outcomes aren't algorithmic systems that automate discretion and surveil us, but eliminating the for-profit insurance industries that rely on them. Maybe what we need to address mass poverty isn't data, it's to dismantle the mechanisms of mass extraction that are increasingly powered by economies of surveillance. Maybe what we need to make the criminal justice system less racist isn't more data to feed into predictive policing algorithms, but to abolish the police. By discounting techno-solutionism as an answer to systemic problems, we might provide space to refocus on their root and develop technologies that *support* that work.

Governments and information conglomerates will not turn away from universalizing surveillance systems by seeing the error of their ways from some ethical appeal. Instead vulgar linked data is a practical strategy intended to mitigate immediate harms while building a plausible alternative. In the immediate future, we will need to contend with mass disempowerment from absence of effective means of organizing information as LLMs flood the internet with junk. Rather than leaning into the ploy and increasing our dependence on platformatized information systems,

vulgar linked data provides an alternative in social proof and collective information organization. We can counter the lonely world of consulting our LLM crystal ball by building systems that let us consult each other. We can counter the infinite surveillance of knowledge graphs of everything with systems that give us control of our own information. Though the technologies might be superficially similar, their effects are diametrically opposed: one approach seizes informational power for the commons, the other concentrates it in the hands of information conglomerates.

Public linked data projects like the Translator and the OKN can be reoriented towards building an informational commons rather than a string of platforms and unifying ontologies [278] . The nearly-unique position of publicly funded research projects not beholden to the profit motive should not be wasted. Rather than pursuing public-private partnerships, can we reorient our research infrastructure development projects to make use of the expertise of disaffected engineers who would do *anything* except spend their lives optimizing ad clicks? There are many of these "ethical engineers" already working on the Translator and OKN projects. We could re-situate our data infrastructure projects as a revitalization of the longer history of liberatory technology movements like the early semantic web, avoid the "hollow middle" of the platformatized web, and maybe even realize some of the loftier ambitions of public infrastructures for the public good.

We face a stark choice for our future. The Cloud is circling, will it eat us alive? Will we build a space of universalizing knowledge graphs that allow the seamless linking and trade of every element of our society, powering algorithmic systems from information organization through medical systems, governance, and policing? Will we continue to let information conglomerates farm us for our data and feed it back to us, reprocessed, as Content and Knowledge™? Will we be hooked by the lip by barbed convenience that promises us magic, but delivers us only greater surveillance, control, and dependence? Will our attempts at resistance only ever amount to a never ending treadmill of startups and publicly-funded projects that can't break from the gravitational pull of The Cloud Orthodoxy, retreading its worldview of asymmetrical power concentration, inevitably shuttered or bought as they fail to compete on the same territory as the information giants?

Or will we build a better world?

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