From Data Leverage to Data Co-Ops: An Institutional Model for User Control over Information Access

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Internet companies derive value from users by recording and influencing their behavior. Users can pressure companies to refrain from certain invasive and manipulative practices by selectively withdrawing their attention, an exercise of data leverage as formulated by Vincent et al. Ligett and Nissim’s proposal for an institution representing the interests of users, the data co-op, offers a means of coordinating this action. We present one possible instantiation of the data co-op, including the Platform for Untrusted Resource Evaluation (PURE), a system for assigning labels provided by untrusted and semi-trusted parties to Internet resources. We also describe PURESearch, a client program that re-ranks search results according to labels provided by data co-ops and other sources.

CCS Concepts:
• Security and privacy → Human and societal aspects of security and privacy; Economics of security and privacy; Social aspects of security and privacy; Usability in security and privacy; • Social and professional topics → Computing / technology policy; Computing / technology policy; • Information systems → Information retrieval; World Wide Web; Reputation systems; Social tagging systems; Open source software.

Additional Key Words and Phrases: data leverage, data co-ops, user control, content filtering

1 INTRODUCTION

1.1 Data Co-Ops

The Data Co-ops initiative of Ligett and Nissim [11] is a wide-ranging, multi-institutional effort aimed at exploring the relationships between Web users and digital platforms. During the past decade, a number of smaller-scale initiatives have focused on issues like collecting higher-quality data, (re-)gaining individual control over personal data, (re-)establishing trust in the online information environment, generating rich data for research purposes, etc. Each of them addressed one or more specific shortcomings of the status quo, e.g., privacy risks, unrealized potential of data, individuals’ receiving limited value in exchange for their behavioral data, and lack of opportunities for public governance of digital creation. By contrast, the Data Co-ops initiative seeks more broadly to address, in a technologically comprehensive fashion, users’ privacy concerns and the potential to tap as-yet-unrealized value in users’ behavioral data.

In our formulation, a data co-op is a membership organization that provides client software, a means of resource discovery, and technical support. There are many possible revenue models for such an organization, the simplest of which is to have the members pay dues. A data co-op could provide means for users to communicate or publish content, such as digital identities and hosting resources. Thus, in the short run, the client software provided by data co-ops as we conceive them would advance Ligett and Nissim’s goals of increased user privacy and more widely distributed value creation. Longer term, a data co-op could provide the means to participate fully in a new network, based on an improved web architecture, as the network grows.

As a first step, we have created a tool that allows co-op members to shape their own processes of resource discovery on the existing Web.

1.2 Implicit User-Provider Negotiations

When a user interacts with an Internet service under typical market conditions, the user and the provider both want to maximize the value they derive from the interaction while minimizing costs. The interests of the two parties are aligned...
in some aspects, such the desire to meet the needs of the user so that she continues to use the service. In other aspects, their interests conflict; for example, in an ad-supported service, the provider wants to maximize the data collected about the user, the time and attention spent on ads, and the capacity to influence user behavior, but the typical user wants to minimize these things.

The adversarial component of this relationship leads to an implicit negotiation: Users want to fulfill their needs while offering the provider only enough value to sustain the service. The provider wants to maximize value extraction, while offering the user only enough value to motivate her to continue to use the service. The strong market positions of many of today’s providers, together with the relative indifference and atomization of users, causes these interactions to tend toward the latter extreme.

This negotiation resembles that between buyers and sellers, and between employees and employers (buyers and sellers of labor). In the same way that unions and consumer cooperatives can shift negotiations in favor of employees and consumers, data co-ops could shift these implicit negotiations over data, attention, and services in favor of users, leading to services that are less invasive, manipulative, and addictive, as well as more useful and reliable.

Although a data co-op could take many different approaches to achieving this goal, our current focus is on technical interventions. In particular, we consider the use of labels to direct traffic towards well behaved pages, services, and other network resources and away from poorly behaved ones.

### 1.3 Types of Intervention and Prospects for User Control

Efforts to address the harms of mass data collection have come in many forms: technical interventions such as Tor [7] and Pretty Good Privacy [8], legal interventions such as the European Union’s General Data Protection Regulation, and interventions by advocacy organizations such as the Electronic Frontier Foundation’s “report cards” and the Free Software Foundation’s promotion of free software. These categories are not strictly disjoint: Any non-technical intervention requires technical efforts to implement, and any technical intervention requires non-technical efforts to support its use.

In the context of a data co-op, the most interesting approaches involve negotiating with service providers (implicitly or explicitly) to offer services in a certain way, and facilitating the use of certain client software by co-op members.

It is helpful to examine the free-software norm in view of the dynamic described in the previous section. Free software offers a protective mechanism against anything that the user would not want a program to do, because users can modify the program or pay someone to modify it for them. However, this requires nearly boundless resources (while users do not even have time to read the terms of use for most services), and modifying client software can introduce incompatibilities with the server.

The shortcomings of the free-software norm are illustrated by the evolution of the Web. As the Web grew more complex and more dominated by huge companies, the complexity of browsers reached a point at which even a free browser like Firefox is beyond the control of users, because it requires a large team of developers to make changes without breaking things. Even if this barrier were overcome, many websites require JavaScript, which is often obfuscated. Even if you did examine the JavaScript code on every website that you visit and modify it to prevent needless data collection or manipulative user interface elements, these changes could break the website’s functionality.

The Web example also demonstrates that effective control over what data are sent to the server requires regulation of the entire client program, not just the network protocol. HTTP was designed for simple hypertext, which lacks many of the data-collection capabilities that modern websites employ, but HTTP can still transport tracking scripts that are
run by a browser engine and report behavioral data back to the server (also via HTTP). Designing the protocol for simple hypertext did not prevent these innovations.

For a group of users to maintain control over the client program, the client code that is specific to a service provider should be minimized. This could be accomplished by keeping to declarative-markup languages, where it is easy to understand which user actions cause data to be sent to the server and what data are sent.

While users still depend on client software that accommodates data collection and other harms, labeling can allow users to preferentially use less harmful sites. This approach also provides a path to gaining control over the client software by filtering out resources that require software developed by unaccountable third parties.

Paper outline
In Section 2, we situate this work within the FAccT research agenda and present related work. In Section 3, we describe the Platform for Untrusted Resource Evaluation (PURE), a framework for assigning labels to online resources, and PURESearch, a tool that re-ranks search results according to PURE labels provided by the user and semi-trusted third parties. In Section 4, we argue that a data co-op’s offering PURE labels and related software to its members would represent a good value proposition and thus that widespread adoption of PURE or something similar is plausible. Finally, Section 5 concludes the paper and discusses future directions.

2 RELATED WORK
We begin this section by situating data co-ops and PURE within the broader FAccT agenda, paying particular attention to the work of Vincent et al. on data leverage [17]. We then briefly discuss three other areas of research that our work draws on.

2.1 Data Co-ops and the FAccT Agenda
Sociotechnical systems play a central role in the FAccT community’s goal of achieving fairness, accountability, and transparency in the online world. Roughly speaking, sociotechnical systems are technologies that support and influence people’s daily lives by taking a multidisciplinary approach. PURE is a sociotechnical system that seeks to alter the balance of power described in Section 1.2 so as to better position users in their implicit negotiations with providers. As noted in Section 1.3, the sociotechnical approach is the natural one to take when trying to increase users’ control over their behavioral data, because social mechanisms intended to increase control will need technological instantiation, and technical mechanisms will not be adopted unless they are enforced legally, incentivized financially, or supported by social trends or norms.

The potential effectiveness of data co-ops and our particular approach to them can be understood and evaluated using the data-leverage framework of Vincent et al. [17], the goal of which is to “highlight new opportunities to change technology company behavior related to privacy, economic inequality, content moderation, and other areas of social concern.” Three levers that are available to users are identified in [17]: data strikes, in which users withhold or delete data to reduce the efficacy of an organization’s data-dependent technologies; data poisoning, in which users insert inaccurate or harmful data into an organization’s data-dependent technology; and conscious data contribution (CDC), in which users give their data to organizations they support. Data co-ops can provide their members with data leverage. In particular, they can manage labels associated with websites, thus effectively subjecting certain sites to boycott; in this way, co-ops can coordinate data strikes, data poisoning, and CDC by their members. Labels also allow this point of
leverage to be used more fluidly and continuously by subtly steering users away from misbehaving sites and towards more favored ones.

Pentland and Hardjono [4], in work that is independent of Ligett and Nissim’s, have also put forth the idea that data co-ops can rebalance the world’s data economy.

2.2 Labels

Labels are commonly applied to static content in the context of parental controls, but they can incorporate arbitrary information and be applied to many types of online resources. To protect user data and improve Web usability, labels could encode information about privacy policies, popups, resource usage, compatibility with privacy-protecting client software, and more.

Previous labeling systems such as the Platform for Internet Content Selection (PICS) require labeling services to be trusted: “When publishers are unwilling to participate, or can’t be trusted to participate honestly, independent organizations can provide third-party labels” [14]. This creates a barrier to participation as a source of labels and limits the range of labels that can safely be used.

PURE improves on this by emphasizing labels that can be verified by end users and leveraging user inputs to assign a reputation to each label source. Under this regime, publishers who self-label their content can be held accountable by the ecosystem of users and label sources.

2.3 Data as Labor

Many works, notably those of Posner and Weyl [12] and Arrieta-Ibarra et al. [6], promote the concept of “data as labor.” Currently, corporations that monetize users’ data view those data as their property that they create by providing services to people who use them willingly. Adherents to the data-as-labor school of thought view data as valuable products that users create and that corporations profit from. Their view leads naturally to the goal expressed in Section 1 and in [17]: Rebalance the relationship between the users who create data and the corporations that profit from them so that users have more knowledge about which data are collected, more control over how data are monetized, and more ability to reap the rewards of data-dependent commerce. Data co-ops may thus be viewed as analogous to labor unions, which serve precisely this function in negotiations between workers and their employers. This analogy was drawn explicitly by Pentland and Hardjono [4]; similarly, Posner and Weyl suggest the formation “data unions.”

2.4 Recommender Systems

Recommender systems [9] are widely deployed in social media and entertainment platforms to predict which content will engage the user most effectively. PURE can be seen as an unusual type of recommender system that maximizes the user’s control over what is “recommended.” Typical recommendation systems employ either or both of two broad approaches: content-based filtering and collaborative filtering. Both are similar in some ways to the approach taken with PURE, but neither applies in a conventional way.

Content-based filtering uses a set of predefined labels for each item, such as a database of song attributes used to recommend music. Typically the user gives feedback on each item via binary or unidimensional ratings, and an algorithm builds a model of which labels the user prefers. Our approach is almost the opposite: Instead of predicting which labels a user likes, we predict which labels an item has.

Collaborative filtering recommends content to a user based on similar users’ responses to the same content. Determining similarity between users is almost the same as determining agreement between label sources, and complex
algorithms for collaborative filtering could be used in place of our simple algorithm. The main difference is that we use agreement between sources to estimate the values of labels, not the overall rating for a resource.

Our approach is also distinguished by doing all processing of labels and ratings on the client side, resulting in less transmission of user data.

### 3 RE-RANKING SEARCH RESULTS BASED ON THIRD-PARTY LABELS

As an initial technical intervention, we have developed PURESearch, a tool that re-ranks search results according to labels provided by the user and semi-trusted third parties. This allows data co-ops and their members to direct usage towards certain web resources and away from others, improving the quality of the results and pressuring publishers to follow certain practices.

In the current (simplest) form, PURE labels are uninterpreted strings that can be bound to URLs with an affirmative or negative assertion, depending on whether the label applies or does not apply. A client program is configured to promote resources with certain labels and to demote others, according to the user’s preferences (or a standard configuration received from a data co-op). The client fetches search results from an upstream search engine, and re-ranks them according to label preferences.

Potentially useful labels include `haspopup`, `hasfixednavbar` and `hascookiebanner`, which apply respectively if the page has a popup, a fixed navigation bar, or a cookie banner. Users may want to filter or demote pages with such labels for the sake of usability. Cookie banners also have implications for data collection, as the user may be required to agree to certain terms in order to remove the obstruction from the page. Mass filtering of pages with cookie banners that do not require cookies for their functionality would pressure publishers to remove such banners and only use cookies when necessary.

The aforementioned labels are helpful when using a standard modern web browser, but a more durable solution would be to use client software that doesn’t support unwanted features. Labels such as `noscriptcompat` and `lynxcompat` could apply respectively if the page is compatible with the NoScript browser addon [1] or the Lynx browser [13]. NoScript blocks all scripts on a page, preventing many forms of data collection and reducing resource usage, but this aggressive measure often renders pages unusable. Lynx is a text-mode browser without support for scripts, which has particular utility for the blind by ensuring compatibility with screen readers [16]. Users of NoScript, Lynx, or similar software could improve their browsing experience by filtering out pages that are incompatible with their chosen client software. This improvement of the experience could induce more users to use such software, putting pressure on publishers to accommodate them.

#### 3.1 Search Client Overview

The search interface is implemented as an HTTP service that is intended to run on the client machine. It could be adapted to run on a remote server, but keeping as much as possible on the client side eliminates unnecessary transmission of user data and improves performance and reliability.

We still rely on a remote search engine (an instance of Searx [3]) for results, and query strings are transmitted to the search engine from the user’s IP address. This could be improved by hosting parts of the search engine infrastructure on semi-trusted servers, possibly operated by a data co-op.

Typical usage of the program proceeds as follows:

- The user configures which labels should be promoted in search results and which should be suppressed.
Fig. 1. PURESearch results for "privacy," including auxiliary information for each source. Here, "score" refers to the upstream relevance score and "ascore" refers to the adjusted score used for re-ranking. The tables to the right show the user’s label preferences and the configured sources along with their tier numbers and reputation scores.

Fig. 2. Sidebar for the user to inspect label records for a page and enter their own.
• Label records are retrieved from a list of sources and processed to estimate the degree to which each label applies to each URL (since sources may not be trustworthy and label records may conflict).
• Search results are fetched from a search engine and reordered according to labels and user preferences (see Figure 1).
• When the user views a result, she may open a sidebar to inspect the label data for that URL and enter their own label assertions (see Figure 2).
• Label assertions by the user are treated as ground truth, and the weight given to each source when estimating labels is determined by the degree to which a source’s labels agree with the ground truth. Sources may also be categorized in tiers, allowing sources in higher tiers to serve as ground truth for sources in lower tiers.

3.2 Label Retrieval and Processing

```
Function Reputation(j)
// Input: label source j
// Output: the reputation of j, ranging from 0 to 1
// t_j is the tier of j, with 0 denoting the highest tier
if t_j = 0 then
    return 1
n ← 0
d ← 0
for (i, k, v_{ijk}) such that j has given v_{ijk}, either 1 or -1, in evaluating item i for label k do
    if Expectation(i, k, t_j - 1) > 0 then
        x ← 1
    else if Expectation(i, k, t_j - 1) < 0 then
        x ← -1
    else // Expectation(i, k, t_j - 1) = 0
        continue
    // add 2 when j disagrees with higher tiers
    n ← n + |v_{ijk} - x|
    d ← d + 1
if d = 0 then
    return 0
return max(1 - \frac{n}{d}, 0)
```

Algorithm 1: Estimating the trustworthiness of a label source. Note the mutual recursion with the Expectation function.

For simplicity, a remote label source is represented by a URL, which the client polls for the current version of that source’s labels. Each label source is assigned a tier number, with the user having tier 0, the highest tier, and higher numbers denoting lower, more subordinate tiers.

Label records are stored in text files with one record per line, each record consisting of a label name, a value (1 if the label applies, -1 if it does not), and a URL, separated by tabs. The format is used for remote label sources as labels are fetched as well as local storage of labels from both remote sources and the user.

Labels are processed to establish a reputation for each label source as detailed in Algorithm 1. On the last line of the algorithm, $\frac{n}{d}$ is double the proportion of (label, URL) pairs for which the label source $j$ disagrees with sources in higher tiers, so the reputation of a source is 0 if it disagrees with sources in higher tiers more than half the time.
Function Expectation(i, k, t)
// Input: item i, label k, and tier t
// Output: the expected value of label k for item i, ranging from -1 to 1, based on sources from tiers 0 through t
if t < 0 then
  return 0
if Expectation(i, k, t - 1) ≠ 0 then
  return Expectation(i, k, t - 1)
n ← 0
d ← 0
for (j, v_{ijk}) such that source j has tier t and has given v_{ijk} in evaluating item i for label k do
  n ← n + Reputation(j) × v_{ijk}
  d ← d + Reputation(j)
if d = 0 then
  return 0
return n/d

Algorithm 2: Estimating the applicability of a label.

Function Adjustment(i)
// Input: item i from search results, in this case a URL
// Output: factor by which to adjust relevance score for i
r ← 1
for each label k in user policy do
  if k is favored then
    // t_{max} is the lowest tier, denoted
    // by the highest number
    q ← Expectation(i, k, t_{max})
  else // k is disfavored
    q ← −Expectation(i, k, t_{max})
  if q ≥ 0 then
    r ← r(1 + q)
  else
    r ← r(1 + q/1−q)
return r

Algorithm 3: Calculating the factor by which to adjust the relevance score of a search result.

After fetching search results, label data that are relevant to the results and the user’s preferences are processed according to Algorithm 2 to produce an expected value between 1 and -1 for each (label, URL) pair, with 1 representing certainty that the label applies, -1 representing certainty that it does not, and 0 representing absolute uncertainty. This expected value is an average of the label values from each source, weighted by each source’s reputation.

Each upstream search result includes a relevance score which determines the upstream order of results. We rearrange the results by adjusting relevance scores according to Algorithm 3. Here, q represents the favorability of the item with respect to label k, so that a positive expectation of a favored label yields the same effect as a negative expectation of a disfavored label with the same level of certainty. The running product is multiplied by $1 + q$ for a favorable assessment and $1 + \frac{q}{1−q}$ for an unfavorable assessment, so that an unfavorable assessment cancels out a favorable assessment with the same magnitude.
Note that checks for a zero value of the Expectation function in Algorithms 1 and 2 treat even disagreement between sources in a given tier the same as an absence of labels from that tier. Furthermore, a nonzero expectation from tier $t$ supercedes any lower tiers (with numbers greater than $t$), even if it has a small magnitude indicating uncertainty. Note also that sources with zero reputation are ignored regardless of tiers. These finer points were chosen arbitrarily or for the sake of simplicity, and could just as well have been done differently. Changes to the handling of reputations and tiers could make more sense *a priori* in certain contexts, or simply yield better results.

A proof-of-concept implementation and self-guided demonstration of PURESearch can be downloaded at http://cs.yale.edu/homes/cmalchik/puresearch-0.1.tar.gz.

### 3.3 Possible Extensions

The version of PURESearch presented here is meant to give a clear illustration of the purpose of PURE labels and what it means for label sources and rated items to be "untrusted." Simplicity is necessary in general to maximize the ability of users or trusted technical experts to understand and control the software they run. However, extensions to the current version of PURESearch could certainly improve its usefulness.

Different label processing algorithms, possibly adapted from prior work in recommender systems, could be used for different subsets of label records. For instance, the Influence Limiter of Resnick and Sami [15] limits the capacity for manipulation by a malicious rater able to create a bounded number of sybils. This would be well suited to a special lowest tier of label sources which are imported without manual vetting, possibly including individuals who publish their label records to a public registry.

Labels could have a continuum of values rather than binary 1 or -1, which could signify uncertainty on the part of the label source or ambiguity in the applicability of the label. Values could also include symbols that specify the semantics of the assertion, describing how the label relates to the content rather than just the degree to which it applies. These extensions raise the cost of verification because complex values may take more time to determine than a simple "yes" or "no."

Labels could also refer to properties that can not be verified by an end user looking at the content, such as authorship or copyright status, or aggregate ratings of privacy practices. This would require other accountability mechanisms to make the labels trustworthy. For example, lying about the copyright status or origin of a work could incur legal liability. Unverifiable labels could also be retrieved from trusted sources such as a data co-op with strong internal accountability mechanisms.

Labels could also be extended to apply to classes of URLs as defined by regular expressions, prefixes, or some other method. A naive approach to this would disrupt the ability to add or correct labels based on interaction with a single page; a more nuanced approach could treat a label record about classes of URLs as a series of ordinary label records.

Finally, label sources could be enabled to make higher order assertions about other label sources, enabling delegation, detraction, and third-party vetting. This would warrant careful limits on the types of assertions allowed, to prevent label records from becoming too difficult to understand.

More extensive changes to PURE are discussed in Section 5.

### 4 VALUE PROPOSITION AND PLAUSIBILITY OF ADOPTION

In this section, we explain why we believe that data co-ops and PURE constitute a good value proposition for users and a plausible path to a fairer and more productive balance of power in the data economy.
Ease of use and low overhead

Although many people care about lack of privacy and inability to exploit valuable data that they themselves created, few people care enough about this pervasive unfairness to be willing to put thought and effort into combatting it on an ongoing basis. As the description of “typical usage” in Section 3.1 makes clear, no ongoing thought and effort is required for a co-op member to use PURE. Users need not configure their own search interfaces; they can use the default configuration that is provided and updated by the co-op’s technical staff. Similarly, users may enter their own label assertions, but they are not required to do so.

We expect there to be some users who regularly enter label assertions and, more generally, act consciously to advance the mission of the co-op. A small number of users with technical skills and strong commitment to the cause may join the co-op’s technical staff as paid employees. One sees the same range of engagement in labor unions: Most people who work in unionized industries simply join the union, pay their dues, and reap the benefits of collective bargaining; some are more active in the union’s negotiations with the employer or in its political or social activities; and a few seek paid employment in official union-leadership positions.

An idea whose time has come

As explained in Section 2.1, technical mechanisms like PURE are rarely adopted unless they are enforced legally, incentivized financially, or supported by social trends or norms. For several years, our society has been trending toward resentment of Big Tech and hunger for protection against Big Tech’s predations. Data co-ops can provide protection as well as leverage for users who wish to channel their resentment constructively. Co-ops are also well situated to support socially beneficial norms of online behavior and to provide forums for discussion and evolution of such norms.

Broad applicability

The PURE approach is optimized for flexibility. Labels can apply to any networked resource with a name, and the labels themselves can refer not only to privacy or control of data but to any property that users care about. For example, websites can be labeled according to how well they deal with various forms of harmful content over which there has been recent public concern: false or misleading information that may have contributed to recent political turmoil in many western countries; addictive and manipulative applications and services, which may negatively impact the mental well-being of users, especially teens; and misinformation about COVID19 vaccines.

Labels with varying semantic properties could help address each of these issues. A diverse range of data co-ops could produce or curate labels for different domains and purposes. Labels may also be provided by individuals and other types of institutions; of particular interest might be labels that are computed by technologically sophisticated, large-scale "Internet observatories" that measure and analyze phenomena that cannot be observed by a single user or even a typical co-op, which may be relatively homogeneous geographically or demographically. By using a semantically diverse and powerful range of labels, a co-op could, for example, deploy a singular browser extension that marks certain pieces of content as false or misleading. The more ambitious goal of comprehensively optimizing the Internet experience on behalf of co-op members may also be within reach.

In summary, the PURE labeling framework is transparent with respect to the semantics of each label and the objects that labels may apply to. It can serve a very broad range of uses – not only data co-ops as we have conceived them.
Protocol independence and support for alternative protocols

PURE labels are separate from and independent of the resources they refer to, so the issue of compatibility between a label record and its object does not arise as long as the object has a name. This shields PURE from the burden of maintaining compatibility with the Web as it rapidly evolves. It also makes PURE well suited to alternative protocols such as Gemini [2] and Gopher [5, 10], which have developed niche followings as a result of discontent with the modern Web and the impossibility of maintaining a modern Web browser without significant capital investment.

A data co-op could act as an incubator for an alternative protocol by curating PURE labels and providing client software for the protocol. The concept of a client-side resource discovery tool, illustrated by our PURESearch program, suggests software that displays resources using an alternative protocol alongside the more familiar and numerous resources on the existing Web.

5 CONCLUSIONS AND FUTURE DIRECTIONS

In this work, we have presented the PURE labeling framework as a powerful and flexible way to promote online privacy and usability, and to increase the share of value that users receive from the data that they create. We have also implemented PURESearch, a client-side search tool based on this framework. To meet the need for an institutional and social setting in which to deploy PURE technologies, we proposed data co-ops as they were conceived by Ligett and Nissim [11], and argued that they can play a natural and constructive role in the FAccT agenda.

While the current iteration of PURESearch is designed to improve usage of the existing Web, PURE establishes a basis for much more radical changes to Internet usage. The techniques for supporting alternative protocols discussed in Section 4 could be applied to a new protocol designed specifically for use with PURE and data co-ops.

We believe such a protocol would be well served by a proposed future Internet architecture called Named Data Networking (NDN) [18]. NDN offers a way to make the Internet more useful and reliable, while making it more difficult to collect data access patterns on a mass scale. This is due to in-network caching and the lack of source information in data request packets. A data co-op operating in a geographic locality would be well positioned to operate a set of NDN nodes, eliminating the bulk of external requests for popular content while saving bandwidth and enhancing the user experience.

Immutable named data objects (NDOs), a core component of NDN, also form an attractive basis for labeling. URLs are a rough identifier for content because the content accessed at a URL can change depending on when it is accessed and the IP address or user agent of the requester. In fact, there is nothing preventing a web server from serving different content for each request. This makes URLs a shaky basis for labels that are meant to refer to a particular piece of content. NDOs do not have this problem because they consist of immutable data objects cryptographically bound to a canonical name and the publisher’s public key. Resources organized as NDOs would thus be much better suited to labeling, and dishonest labelers would no longer have plausible deniability when issuing faulty labels.

In addition to a new data transport protocol, we see potential utility in a new semantic hypertext language designed with PURE and data co-ops in mind, particularly with respect to the goal of user control over client software discussed in Section 1.3: The behavior of an HTML document running JavaScript is impossible to determine in a bounded amount of time; bounds on the resource usage of scripts can allow for some reasoning about the properties of a page, but the details remain fundamentally opaque. HTML and JavaScript could be replaced by a purely declarative markup language, giving the client program full insight into what a page is doing. Gemini shares this goal but lacks functionalities that users of the modern Web have come to expect. Such functionalities, which are traditionally left to scripts, could be
replaced by declarative markup with well-defined behavior, giving the user full control over the behavior of the client. Extensions to standard markup could be evaluated and labeled by data co-ops or third parties, with assurances that a markup extension includes no unnecessary data collection or other malicious features.

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