Volume I: Technical and Management Proposal

Cover Page

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Contents

1 Executive Summary

Motivation and Goal: Today's web services – such as Google, Amazon, and Facebook, as well as third-party advertisers less visible to users – collect and leverage user data for varied purposes, including personalizing recommendations, targeting advertisements, and adjusting prices. At present, users have little insight into how their data is being collected or used and how that affects them. This lack of awareness prevents them from making informed choices about the services they use, what they should be revealing to those services and what not, or what protection tools they should use to prevent misuse. Our goal is to develop *user awareness tools* that will help users gain a better understanding of the implications of their online actions by revealing to them concretely how their data is being collected and used by the services to target them. For example, one user awareness tool could reveal what specific data within a user's profile – such as emails, prior browsing behaviors, etc. – are being targeted by each advertisement they receive. Another tool could reveal to a user that she is seeing a differentiated price, and specifically which data within her profile triggered that differentiation. In support of such tools, we propose to build *Hubble*, an extensible, generic, and scalable infrastructure that provides the necessary scientific methods and programming abstractions to facilitate the building of many such user awareness tools. Using Hubble, we will develop and evaluate several user awareness tools, and will study how transparency and awareness can help shape user actions and enable them to better manage their online privacy. Our effort targets *Technical Area #2* (Human Data Interaction) and is *fundamental research*.

Key Technical Challenges: Constructing user awareness tools raises significant and unresolved challenges. First, once data is given out to a service, how can one still track its use? Tracking data in a controlled environment, such as a modified operating system, language, or runtime, is an old problem with a well-known solution: taint tracking systems [16,23,28,74]. However, is it possible to track data in an uncontrolled environment, such as the Web? Can robust, generic mechanisms assist in doing so? What kinds of data uses are trackable and what are not? How would the mechanisms scale with the amount of data being tracked? Second, constructing user awareness tools that do not themselves create new privacy challenges is a difficult challenge. Intuitively, to reveal how data is being used, a user awareness tool needs to monitor that user's data, and perhaps share it with a third party that aggregates data from multiple users. Why should the users trust those tools and the third-party that run them, and how can we minimize that trust? Third, quantifying the effect of user awareness tools on the end-users is an open question. For user awareness tools to be effective, they must not only help educate users – and watchdog organizations like the Federal Trade Commission (FTC) or the Electronic Frontier Foundation (EFF) – about data collection and use, but they must provide useful and auditable actions that users can take to manage their privacy.

Review of Proposed Technologies: Our project will develop both the tools and the necessary scientific methods and infrastructures necessary to increase users' awareness over what happens with their data once they share it with web services. The center piece of our proposal is *Hubble*, the first scalable and extensible infrastructure that provides a series of abstractions for accurately detecting data collection and use for targeting and personalization within and across (largely) arbitrary web services. Hubble's three main research contributions are: (1) leveraging *state-of-the-art statistical methods in unique ways* to accurately detect targeting in black-box services based on experiments with differentiated user profiles, (2) providing an *extensible and dynamic architecture* that enables automatic validation, refinement, and attribution of targeting inferences, and (3) providing primitives for doing targeting inference in a privacy-preserving way.

Using Hubble, we will build a number of useful user awareness tools, which reveal specific aspects about data collection and targeting on the web which may now escape notice by the end users. Those tools include: (1) *CollectionObservatory*, a tool that reveals third-party web content that invisible collects information about users' browsing behaviors; (2) *AdObservatory*, a tool that reveals how third-party web trackers leverage the information they collect about the users – such as visited pages, Facebook Likes, or explicitly shared information – to target ads at them; (3) *DiscriminationObservatory*, a tool that reveals to the end users any differential treatment in the prices or offers they get from ecommerce, lending, and mortgage websites; and (4) *LocationObservatory*, a tool that communicates to users how multiple location records associated with them both relate to their sensitive data (*e.g.,* age, ethnicity) and personalization offered by services.

Current Approaches and Limitations: Our project will create *robust, generic user awareness tools to track the use of personal data at fine granularity (e.g., individual emails, photos, or visited websites) within and across arbitrary Web services.* At present, hardly any such tools exist, and the science of tracking the use of personal Web data at scale and at a fine granularity is extremely limited. Our own recent system, XRay [43], includes some preliminary results that transparency at fine granularity is possible, but does not address any of the significant scaling, privacy, and usability challenges defined above. We have also previously developed TrackingObserver [63] to detect third-party trackers on the web, but it remains limited in terms of the types of data collection it can detect (notable, omitting fingerprint-based trackers) and does not provide information directly useful to end users. Other transparency systems, such as Bobble [71], AdFisher [18], and OpenWPM [24], are either not generic (e.g., Bobble reveals personalization of news and search results on based on a few user attributes) or operate at small scale [18, 71].

Expected Impact: The greatest impact of our work will be to increase user awareness about the implications of their online actions and to provide building blocks for tools that empower users to manage the information that they reveal. We believe that a vital part of protecting private data that users knowingly provide to third parties is to enable non-expert users to *know more*, *take action*, and *verify the results of their actions*. Moreover, we believe that by empowering users, as well as third-party privacy watchdogs, with transparency tools we will help transition the web services world toward a more privacy-aware future. In Louis Brandeis' own words – "Sunlight is said to be the best of disinfectants; electric light the most efficient policeman" [**?**]. Hubble will help bring a new level of oversight and accountability into a very obscure Web world, thereby putting pressure on web services to be more privacy aware. Finally, while this proposal focuses on awareness tools and building blocks for the Web, we believe that our technologies will be applicable to other problems of enterprise and national importance, including being able to reveal how data is being used (or abused) by the parties that obtain it (such as partner enterprises and foreign governments).

Cost, Duration, and Team: Our proposed effort will last 4.5 years (starting on 09/01/2015), with a total cost of $3,960,419. The team are from Columbia University and University of Washington.

2 Goals and Impact

Many of today's pervasive practices that collect and leverage user data are invisible, or at best unexpected, to users. For example, web and mobile applications commonly collect and aggregate information about users (including browsing behaviors, location, and unique identifiers) for the purposes of targeted advertising or other types of personalization [43, 60]. Many of today's users have some notion that this data collection is happening (e.g., through extensive media reporting on the topic [66]) and that they are exchanging some amount of private information for the use of free services (email, search, social media). Indeed, these practices are typically disclosed in terms of service agreements, to which users must technically agree to use an application or service. However, users' understanding of the extent of this data collection, as well as its use and implications, remains limited and abstract [68]. **Thus, a necessary goal on the path to protecting private data that users knowingly provide to third parties is to help non-expert users *know more*, *take mitigating actions*, and *verify the results of their actions*.**

To this end, we propose the design, development, and evaluation of a new generation of **user awareness tools** that help non-expert users better understand and monitor the data collected about them and how it is (or might be) used. We identify a set of goals for effective user awareness tools:
1. *Actionability:* Beyond just displaying information about private data collection and use to users, an effective user awareness tool must be actionable — that is, users must be able to do something with the information they learn. Though it can be useful to simply inform users about the amount of data invisibly collected about them to build support for broader efforts to manage such collection, such solutions have limited effect on users at present.
2. *Auditable results:* Once a user takes an action to mitigate data collection or use based on increased awareness, it is important that the user be able to audit the results of his or her action. In other words, users should be able to answer the question: "Are my tools, actions, and mitigation strategies actually doing what I expect?"
3. *Attribution:* An effective user awareness tool should allow users to attribute data collection and use to the specific entities responsible. For example, when multiple third-party trackers are loaded on a web page, an effective tool would allows users not just to identify their presence but to trace back particular page content (e.g., ads) to the responsible third party. This attribution helps with both actionability and auditable results, as it helps users understand who is (or is not) doing what.
4. *Awareness about use, not just collection:* We must help users understand not just what data is collected about them, but also potential and actual uses of that data. We cannot expect that end-users will be able to extrapolate all possible implications of revealing or allowing certain data to be collected. Our user awareness tools must help users understand and anticipate these implications so they can make informed decisions about which data they are willing to share with whom.

There are many aspects of personal data on the Web that are interesting to reveal. For example: can we build tools to reveal to users how their data is leveraged to target ads or recommendations, whether shopping or mortgage sites are using their browsing histories or Facebook profiles to adjust their prices, whether their purportedly encrypted email service is actually decrypting their emails and using the data for its marketing purposes, or whether a service shares their data with third parties – and then how those third parties use the data? For each case, can we reveal exactly which specific data item (or items) that they share with their services – such as emails, documents, locations, or previously visited websites – trigger the specific ads, recommendations or prices? Such visibility, we believe, would be beneficial to the end users to better understand the implications of their online actions, as well as to assess the effectiveness of any defenses they apply.

Unfortunately, constructing user awareness tools that reveal these and many other potentially interesting aspects about the data's journey on the web is extremely difficult today, due to a lack of scientific methods to both *detect* data collection and use and *surface* it to end users in effective and actionable ways. For example, a number of tools exist that visualize third-party web trackers (e.g., `ghostery.com`, `mozilla.org/en-US/lightbeam/`). While these tools can help users understand how many trackers they encounter in their browsing experience, and allow users to block individual trackers, they lack desirable properties including attribution (e.g., users may know that a tracker is present on a webpage, but not which parts of the page were affected). Finally, hardly any tools exist today, which can reveal to users how their data is being used by the services that collect it. A few efforts have recently been made (e.g., AdReveal [46], Bobble [70], AdFisher [18], and our own XRay system [43]), but they are all primitive in both detecting data use by Web services and effectively surfacing that information to the end users.

Thus, **our specific goal is to develop not only the first *effective and actionable user awareness tools* that reveal specific aspects of personal data collection and use on the web, but also *the science and infrastructural support* for building many such tools in the future**. More specifically, as part of this program, we will develop *Hubble*, an extensible, generic, and scalable infrastructure that will provide the necessary scientific methods and programming abstractions to facilitate the building of a new generation of user awareness tools for for the web. Hubble's two main scientific contributions are: (1) an *extensible, scalable, and dynamic architecture* that leverages statistical methods in unique ways to accurately detect tracking, targeting, personalization, and discrimination in black-box services based on observations of differentiated user profiles, and (2) primitives for *effectively surfacing to users* information about detected data collection and use.

To drive Hubble's design, we will develop and evaluate at least four user awareness tools, which leverage and inform Hubble's programming abstractions to detect and visualize various aspects about online data collection and use for targeting, personalization, and discrimination. The specific tools are: (1) *CollectionObservatory*, a tool that detects and visualizes third-party web content that invisible collects information about users' browsing behaviors; (2) *AdObservatory*, a tool that detects and visualizes how third-party web trackers leverage the information they collect about the users – such as visited pages, Facebook Likes, or explicitly shared information – to target ads at them; (3) *DiscriminationObservatory*, a tool that detects and visualizes personalized content present on arbitrary websites, with a particular focus on personalized prices or offers on ecommerce, lending, and mortgage websites; and (4) *LocationObservatory*, a tool that detects geo-based targeting and interpret it in terms of demographic attributes.

If successful, our work will lay the first scientific foundations and technology for comprehensive tracking of data collection and use within and across the Web. We foresee multiple domains of impact for our technology. First, by increasing user awareness of how their data is being used on the Web, we hope to make users more mindful of service selection and usage. Second, by enabling robust and scalable transparency tools, we can empower privacy watchdogs – such as journalists, Federal Trade Commission (FTC) investigators, consumer protection agencies, or internet freedom groups (e.g., EFF) – to keep this giant, complex, and ever-changing Web in constant check to discover any abuses. Third, by enabling transparency at scale and from the exterior, we hope to usher in a new era of voluntary transparency and responsible data behaviors by the web services themselves. Fourth, we believe that our work can integrate well with personal data protection technologies that will be developed as part of the Brandeis program, including TA1 and TA2 technologies. We discuss our vision of such integration in Section 3.

3 Collaborative Research Team Concept

The transparency and awareness tools we propose to build and evaluate will integrate very closely with other TAs. In particular, our tools can help incentivize adoption of TA3 systems that are built using protection mechanisms developed by other TA1 and TA2 performers; this is achieved by effectively informing users of privacy implications/threats of systems driven by user data. Through extensive user studies, we will evaluate how users' mental models of digital threats and their behaviors are impacted by increased transparency and awareness of risks, and by the presentation of viable alternatives to existing privacy-risky systems. To support this effort, we will require specifications of how TA1 and TA2 protection tools can prevent specific privacy risks that we may expose via our transparency and awareness tools, and how they are deployed in TA3 systems. We will also require specifications of how TA3 systems make use of sensitive user data. For instance, does a privacy flag in a web browser mask sensitive user attributes such as race, religion, and sexual orientation from being exposed to advertising networks via browsing behavior? Can the protection tools prevent recommender systems from leaking user-supplied preferences to other users? If we can expose such specific privacy risks in existing systems using our tools, and at the same time guarantee that alternative privacy-hardened systems mitigate those risks, then we will be in a better position to inform end-users of concrete risks and viable alternatives. Our findings will also help assess the effectiveness (or ineffectiveness) of TA1 and TA2 protection tools, and will ultimately help iterate on and improve those designs.

4 Technical Plan

Our project will develop both the first *tools* and the first *extensible, scalable, and robust infrastructure* needed to track data use in the uncontrolled Web. Our specific plan involves efforts in three thrusts, which we will execute in parallel. First, we will develop the *Hubble infrastructure and programming abstractions*; it will provide a set of highly reusable and scalable components that will facilitate the building of transparency and user awareness tools to lift the curtain on how personal data is being used. Second, we will build a set of robust, scalable, and usable *transparency and user awareness tools* that leverage those abstractions and enable users, journalists, and investigators to obtain visibility into Web services' data uses. Third, we will leverage these tools to run *measurement studies* of various data-driven platforms, such as targeted advertising ecosystems, online trackers, and online price discrimination. These studies will increase awareness, and perhaps help uncover examples of data mistreatments, which will provide the grounds for an informed societal argument on the need for increased voluntary transparency by the services.

4.1 Thrust 1: The Hubble Transparency Infrastructure and Abstractions

Hubble and its abstractions will support the development of transparency and user awareness tools that reveal aspects about data use on the web. More specifically, Hubble will support the development of any tool that aims to reveal which specific data *inputs* – such as emails, documents, Facebook Like's, or previously visited websites – are being used to target which specific service *outputs*, such as advertisements, recommendations, or prices. Hubble offers an infrastructure and programming abstractions that can identify targeting at great scale (in the number of inputs, outputs, and services that are being audited), with solid statistical guarantees, and with privacy-preserving properties. Examples of tools that could benefit from Hubble support include AdObservatory, DiscriminationObservatory, and a number of web transparency tools that others have recently built (e.g., [18, 30, 31, 50, 71]).

4.1.1 The Hubble System and Core Abstractions

At the highest level, Hubble will operate as follows. To reveal which specific inputs (e.g., emails or visited websites) in a user's profile were used to target a particular output O that the user is shown (e.g., an ad), Hubble relies upon *observations* of that same output O in the context of other

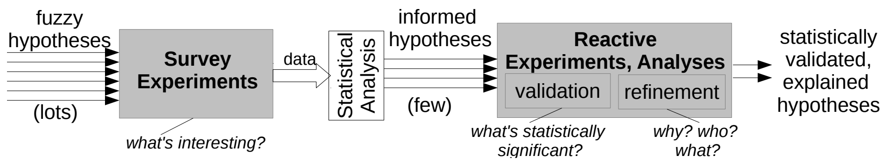


Fig. 1: **Example Experiment Workflow in Hubble-based Transparency Tool.**

user profiles with different sets of inputs. For example, if an ad O is often shown to user profiles with a particular website W in their histories, but is never shown to profiles that lack W, then it is plausible that the ad targets that website. Hubble applies statistical methods to infer such *targeting hypotheses* of outputs on specific inputs or combinations of inputs.

The decision of what inputs and outputs are interesting to relate, as well as how the observations required to make the targeting inferences are obtained, is entirely dependent upon the developer of the transparency tool. The observations, for example, could be obtained directly from a population of end-users (e.g., through a browser plugin that monitors users' browsing and the ads they receive and reports them to Hubble) or through a controlled experiment where user profiles are managed automatically and assigned inputs in a controlled way so as to maximize inference power. Hubble supports both use cases, and transparency tool developers decide what use case they wish to support in their own tools. Regardless, Hubble abstracts out these tool-specific aspects into a core abstraction: *a targeting experiment* (or simply *an experiment*). An experiment specifies the inputs, outputs, and differentiated profiles, as well as an observation collection procedure, along with the type of inference to apply (e.g., correlation, causal, and others).

A transparency tool is constructed as *a workflow of experiments* that build upon each other's findings to reveal increasingly complex aspects about online targeting. For example, AdObservatory reveals not only reveals which websites in a user's browsing history trigger specific targeted ads but also attributes each targeting to a specific tracker that most likely was responsible for it. While Hubble will not impose a particular workflow structure, we find one design pattern particularly useful in practice and propose to develop programming abstractions to support it.

Fig.1 shows this pattern and two abstractions designed to support it. The developer structures her tool as a set of large-scale, survey experiments each followed by several finer-grained, reactive experiments. Hubble's survey experiment abstraction lets the developer simultaneously evaluate many possible targeting hypotheses, using powerful ideas from compressed sensing [11, 20] to maximize statistical efficiency with limited and sparse observations. Data from the experiment (reports of output observations in particular user profiles) feeds into the statistical analysis engine, which yields a set of *plausible, informed hypotheses* (specific inputs or sets of inputs that appear targeted by specific outputs).

Several of these hypotheses may have confidence scores that are high enough to suggest some effect but perhaps not high enough to reveal to an end-user (erroneous targeting may affect tool credibility). These plausible hypotheses are hence used to trigger a set of follow-up experiments, called *reactive experiments*, that focus on specific hypotheses and attempt to either boost their confidence (*validation experiments*) or provide a more detailed investigation (*attribution experiments*). Validation experiments can typically be less statistically complex than survey experiments and thus afford more statistical power. For example, a validation experiment may focus on just the specific inputs that have are believed to have triggered the output, and this number may be far fewer than the original number of inputs from the survey experiment. Attribution experiments are also informed by survey results, and typically pipelined after the validations, and they attempt to pose more in-depth questions about the plausible hypothesis. For example, in AdObservatory, we may follow an initial survey experiment with *attribution experiments* that considers different trackers that may be responsible for ad targeting.

Reactive experiments are defined by the developer by implementing Hubble's API, which lets programmers define under what conditions certain experiments should be run. Hubble executes the workflow in real-time according to the developer's specification and returns a set of statistically validated and explained targeting hypotheses. Section 4.2.1 shows a concrete example of the experiment workflow that we plan to leverage in AdObservatory.

4.1.2 Statistical Correlation and Causal Inference

The Hubble infrastructure requires mechanisms for both generating and validating plausible targeting hypotheses. The possible causes for ad targeting and tracking in a given system are myriad, and it is intractable—for both human users and computational methods—to exhaustively consider all of the possibilities. Unfortunately, many existing techniques designed specifically for finding causes of ad targeting in various settings (e.g., [18, 43, 71]) are generally fragile, inflexible, and do not scale with large numbers of potential targeting hypotheses.

We will develop a rigorous and scalable statistical methodology for generating and testing targeting hypotheses based on Hubble's primitives for conducting *randomized targeting experiments*—which permit strong causal findings of targeting—as well as using *observational data* of real user profiles. These findings will help inform users of the privacy implications of exposing sensitive information to online systems/trackers.

Basic approach to generating targeting hypotheses. We will first develop a method based on linear regression to discover putative targeting hypotheses from experimental data collected by Hubble. A linear regression model posits that a real-valued *output variable* y is determined by a linear combination of p *input variables* $\mathbf{x} := (x_1, x_2, \ldots, x_p)$, plus a random mean-zero noise ε. (Categorical variables are expanded using "dummy variables".) The linear model is written as $y = \sum_{i=1}^{p} w_i x_i + \varepsilon$, where $\mathbf{w} := (w_1, w_2, \ldots, w_p)$ is the *regression coefficient* vector. Given n vectors of input values $\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(n)}$ together with corresponding output values $y^{(1)}, \ldots, y^{(n)}$, the goal of linear regression is to estimate the regression coefficients $\mathbf{w}$.

In a basic Hubble application for a particular service (e.g., ads targeting), each vector of input values corresponds to a user profile. The variables in $\mathbf{x}$ correspond to either $\{0, 1\}$-valued indicators for the possible targeting inputs—such as the websites that the user has visited that might be used to target ads—or uncontrolled variables associated with a user profile (e.g., time-of-day of experiment, IP address of client used); the output variable y encodes a particular measured output of an online service or system (e.g., number of times a particular ad was displayed to the user). We will use the regression coefficients $\mathbf{w}$ to generate plausible targeting hypotheses based on the coefficients' magnitudes. The targeting inputs associated with large regression coefficients are then, in some combination, hypothesized to cause differences in the observed output.

Using sparse linear regression. The basic regression approach for generating targeting hypotheses is not scalable because there are likely many possible targeting inputs—and combinations thereof—that may *a priori* have causal effect on the output. Standard linear regression approaches will require at least as many user profiles as there are possible inputs (i.e., $n \geq p$), regardless of how many of these inputs are actually responsible for the targeting output, and thus result in costly and time-consuming experiments.

We propose to use *sparse linear regression* methods, which are effective at estimating $\mathbf{w}$ even when $p \gg n$, as long as $\mathbf{w}$ is sparse—i.e., has only a few non-zero entries. This sparsity assumption entails that only a few input values are, in combination, correlated with the output. A well-established method for sparse linear regression is Lasso [67]. Under certain conditions on the n input vectors, which we ensure are likely to be satisfied *by construction* of our profiles, Lasso accurately estimates $\mathbf{w}$ as long as $n \geq O(k \log p)$, where k is the number of non-zero entries in $\mathbf{w}$ [9]—i.e., the number of input variables potentially correlated with the output. In fact, this collection of $O(k \log p)$ input vectors supports the *simultaneous* estimation of multiple coefficient vectors for different outputs (e.g., different ads); this remarkable phenomenon (related to compressed sensing [11, 20]) enables highly scalable experiments for generating targeting hypotheses.

Validating targeting hypotheses. To verify whether a targeting hypothesis is valid, we propose to use a two-stage protocol commonplace in statistics and machine learning. We employ two groups of user profiles: the first group ("training set") is used for generating plausible targeting hypotheses, and the second group ("test set") is used solely for testing the hypotheses. We will use tests that provide measures of statistical signifiance in the form of *p-values*. We note that when the input values involved in a targeting hypothesis are randomly assigned to the user profiles in the test set, then we are able to assess the *causal effects* of these inputs on the output.

Complex targeting hypotheses. In many cases, some additional exploratory experiments can be beneficial for discovering certain complex targeting behaviors. First, targeting inputs may naturally partition into semantically meaningful groups (e.g., health websites, travel websites) that are targeted as a group rather than as individual inputs. Using correlation metrics, we can discover these input groups [6] and then exploit group-level sparsity in our approach for discovering targeting hypotheses; this ultimately may reduce the number of user profiles needed to accurately estimate regression coefficients [38]. Secondly, we may seek out higher-order combinations of inputs that are potentially relevant, and include these combinations in the regression [5]. This would will enable discovery of more complex targeting hypotheses. To support these exploratory experiments, we propose a multi-stage approach whereby groups or higher-order inputs are constructed in a first stage, targeting hypotheses are generated in a second stage, and finally hypothesis testing is conducted in the final stage.

Targeting hypotheses from observational data. Thus far, we have discussed approaches to generating and validating causal targeting hypotheses. However, these methods are based on synthesizing user profiles that may be far removed from any given real user's profile. Therefore, we believe it will be beneficial to also consider targeting hypotheses based solely on actual users' profiles. We will explore and evaluate techniques for estimating causal effects from this *observational data* based on assumed casual models [56], and also apply techniques for non-causal targeting hypotheses (e.g., hypotheses of correlations or other measures of associations) that are simply annotated with a familiar correlation-vs-causation disclaimer. For these correlation hypotheses, we will also aim to discover latent factors like population stratification structure that may induce or mask correlations between inputs and outputs. Accounting for these latent factors may produce more reliable findings and increase power to discover targeting behavior that only manifest in subpopulations.

4.1.3 Privacy-Preserving Transparency Protocols

A pressing need immediately arises as Hubble interact with personal data: "Does Hubble itself introduces new privacy threats?" In one scenario, a user hosting her email online wants to audit the use of her data, but *only if* a tool built using Hubble guarantees no additional exposure to identity-theft. Alternatively, some members of a service may join an auditing tool for data usage *only if* it guarantee that none of their specific individual records will become known to each other. Hubble adresses that need by design under one important disclaimer: it is *not* meant to keep data private *from the service whose data use is under scrutiny*. Indeed, in many motivating scenarios, the service already received user data. Moreover, as Hubble has to interact with the service, doing so without revealing the inputs remains hard.

Privacy objectives and a new architecture. We aim to prevent the two remaining risks: data disclosure by Hubble itself via its building blocks or APIs, and disclosure from the tools built on top of Hubble. Formally, users should receive *a strong privacy protection*: if we index possible inputs databases as $D_1, D_2, \ldots$ by j, we want that the state of Hubble at anytime $\mathcal{M}(.)$ satisfies the following statistical guarantee [45]: $\forall \omega\ ,\ \forall i = 1, \ldots, m\ ,\ \sum_j c_i(j) \mathbb{P}\left(\mathcal{M}(D_j) = \omega\right) \leq 0\ .$ where m and $c_i(j)$ are publicly known and characterize privacy guarantee (*e.g.,* , this satisfies ε-differential privacy if $\mathbb{P}\left(\mathcal{M}(D_j) = \omega\right) - e^{\epsilon}\mathbb{P}\left(\mathcal{M}(D_{j'}) = \omega\right) \leq 0$ whenever j and j' only differ by one record). But the motivation of Hubble requests two other objectives: *overhead cost*, especially on the client side, and *flexibility*. For the sake of comparison, let us review a mechanism we separately designed inside another research effort to tracks keyword based targeting among untrusted users. To avoid the prohibitive cost of running Hubble locally under each user's control, a custom made design leverages efficient zero knowledge protocols for addition and property testing [21], and privacy preserving statistics [25]. That architecture offers the guarantee above (assuming our code and implementation is trustworthy), it has manageable but significant performance cost for both users and the infrastructure, it offers no flexibility beyond this specific use case. Hubble, in contrast, addresses a more general case using a radical new design based on a new trust model. We assume that, in addition to the provider, and Hubble, a third entity is trusted by users to maintain a database that answers queries within the guarantee aforementioned. Note, however, that this "data bank" is *not* a transparency agency and it may not even be aware of the existence or role of Hubble. Let us immediately justify why this ideally addresses our needs: First, the user may not trust any of our custom-made code *at all* to receive privacy. Second, the overhead on the user side is reduced to the absolute *minimum* Above all, the key advantage of this architecture is a unique *flexible modularity*. No matter *how* respectively Hubble and the data bank decides to operate, as long as Hubble's accuracy and the bank's guarantees hold, transparency and privacy are jointly achieved. All that remains is to prove that those are compatible.

Before more details, let us mention recent solutions proposed to the users for such data banks. All are motivated by a recent trend treating personal data as a new class of digital asset [1], which makes Hubble an ideal complement: research prototypes, *e.g.,* [19, 52], grassroot initiatives *e.g.,* `lockerproject.org`, commercial services *e.g.,* `personal.com, aircloak.com` exist. We obtained, for the scope of this research, a free access to the latter service for testing purpose, and agreement for free accounts to be used by volunteers in our first trials. Note that we only need this service to operate with Hubble to access user data, all other web-transactions are otherwise unchanged. A separate question is whether such data banks can be conveniently used on the web but it is not our concern.

Research hypotheses and methods. What remains as a key research challenge is to prove that statistical queries under the above privacy condition allows Hubble to operate with high accuracy. During Phase 1, we will build a proof of concept with a limited set of inputs, *i.e.,* a small dictio-

E1: Website targeting experiment:
– inputs: websites with ads and/or sensitive material
– outputs: ads observed
– uncontrolled_vars: time, ip.
– const: pages visited on websites.

E2: Targeting validation:
– registered after all E1 hypotheses
– let: w_in = website ad targets; w_out = website where ad appears.
– inputs: w_in, w_out.
– outputs: ads observed.
– uncontrolled_vars: time, ip.

E3: Tracker attribution:
– registered OnNewHypothesis(ad, w_in, confidence) if confidence >= 99%.
– inputs: trackers on w_in, w_out.
– outputs: ads on w_out.
– uncontrolled_vars: time, ip.
– const: always visit w_in, w_out.

Fig. 2: **AdObservatory Experiment Design.** Workflow: E1 → E2 → E3.

nary of 50 keywords, 50 sites visited etc. and two data bank implementation: A simple generic data release leveraging exponential mechanism [48] and multiplicative update [32], and the more complex architecture offered by `aircloak.com`. We expect loss of coverage and more infrastructure resource in comparison to previous custom made solution. Our hypothesis to validate is that Hubble brings flexibility at sustainable cost. Phase 2 will considerably extend the design, as a decade of research proved that leveraging specific data constraints [34, 35, 41, 42], or groups [40] is highly beneficial. We will take full advantage of the modularity of Hubble to inform new data bank design scaling to larger inputs catalogs (up to 1,000 of keywords, possibly more) and also simultaneously explore differentially private pre-processing steps of data mining such as k-means clustering [49] and dimensionality reduction [12, 14]. Phase 3 is dedicated to sustain scaling with two most promising but advanced scenario: exploiting structures of location data (as, for different purposes, [4, 15, 51]), and leveraging multi-stage experiments and data access to increase accuracy.

4.2 Thrust 2: Transparency and User Awareness Tools

4.2.1 AdObservatory: Revealing Targeting in Online Advertising

The first tool we propose to build atop Hubble is *AdObservatory*, which leverages Hubble's abstractions to reveal to the users how they are being targeted by online advertisers. For each ad that a user encounters while surfing the Web, AdObservatory, a browser plugin, will tag the ad with two pieces of information: (1) which specific website(s) in the user's browsing history that caused that ad to be shown and (2) which specific tracker(s) that witnessed the users' visits caused the ad to be shown. These pieces of information correspond directly to the goals we established for user awareness tools (see Section 2): (1) enables *targeting awareness* and (2) provides *attribution*.

Fig.2 shows an experiment workflow that we might use for AdObservatory. It consists of three Hubble experiments: E_1 is a broad survey experiment to formulate rough targeting hypotheses for each ad; E_2 is a smaller experiment to validate the targeting hypotheses generated by the survey and prune out ad erroneously labeled as targeted; E_3 is an attribution experiment to determine which specific trackers contributed to the targeting of cross-domain ads discovered by E_1 and confirmed by E_2. In more detail, E_1 aims to identify what ads are targeting from a huge range of possibilities. In E_1 each input is one of hundreds or thousands of websites in a user's web history. The data collection is either an automated browser (e.g., using Selenium) in the case of controlled experiments using AdObservatory, or a plugin running in users' browser. Regardless, the data collection procedure records as Hubble outputs all display ads observed while visiting web pages. To detect ads on arbitrary pages, we will modify AdBlock to report any identified ad but does not disable it. In addition to collecting display ads, the data collection also records all trackers detected on each site for use in future experiments in the workflow. To detect trackers, AdObservatory will leverage the CollectionObservatory tool we will develop as part of this project. AdObservatory will use Hubble's statistical correlation and causation methods (§4.1.2) to identify which output display ads target which input sites.

E_2 aims to validate targeting hypotheses from E_1 in a more rigorous and controlled fashion. E_2 creates a group of n profiles, half of which get assigned the targeted website. In addition, all of the profiles get assigned the websites on which the ad appeared; excluding the targeted website if the ad appeared there too. Since, our input is the presence of the targeted website in a profile, E_2 is restricted to ads that appear on at least one website other than the targeted. The ads and their respective groups of site validated as targeted in E_2 will be used in E_3. Experiment E_3 is similar uses the same groups of sites as E_2 but uses trackers collected in E_1 as inputs rather than sites. Using the standard Hubble assignment mechanism each tracker is randomly assigned to half of the accounts. The data collection worker used in E_3 drives the profile to all sites in the assigned group blocking trackers all trackers no allocated to that profile.

4.2.2 DiscriminationObservatory: Revealing Online Price Discrimination

A second tool that we propose building is *DiscriminationObservatory*, a tool that leverages Hubble to reveal to the users how arbitrary websites are personalizing their content based on their personal data. A specific use case we are aiming to support is to reveal price or offer differentiation on eCommerce, mortgage, and loan websites based on users' personal information, such as Facebook or Google+ profile information, or web histories purchased from trackers. Many websites today leverage the single-signon capabilities of a handful of giant-scale services, such as Facebook Connect and Google OAuth, to authenticate their users. Upon authenticating a user through Facebook or Google, the websites obtain access to various aspects of a user's profile on these services, and the level of access depends upon the permission level that the website asks for. These pieces of information are often used by the websites to personalize content. For example, Pinterest leverages Facebook Connect to authenticate its users; it requests access to the friend list of a user (among other things) and uses that list to personalize the content it recommends its users. Many other websites do this, and there has been speculation in the media recently that mortgage, loan, and other eCommerce websites might soon start using Facebook Likes and other social information to present the users with differentiated quotes on their websites `http://ti.me/1oPVwqB`. At present, no one knows whether any such websites apply such differential treatment, and (worse) no one can find out, because there are no scalable, robust, and generic tools that can identify this kind of behavior in the wild.

Our goal in DiscriminationObservatory is to *detect* such differential treatment on arbitrary websites and *surface* sufficient information to the end-users and privacy watchdogs. End users may leverage this information to inform their decisions about the offers they receive. Privacy watchdogs can use DiscriminationObservatory to search for websites on the web that discriminate against protected user categories, such as specific races, ethnic groups, or genders. To first order, DiscriminationObservatory will leverage Hubble to obtain and analyze the contents of websites of interest (the Document Object Model, or DOM) from the vantage points of users with differentiated profiles. It will compare the contents of the websites at DOM tree level to identify differences that are consistent with differences in the user profiles. Finally, it will highlight visually any DOM portions that receive differential treatment based on various aspects available in social profiles (e.g., gender, relationship, Likes, friend list, etc.). We will leverage known algorithms for discerning differences between DOM trees (e.g., [26, 72]).

4.2.3 CollectionObservatory: Revealing Third-Party Content and Tracking

A third tool we propose to build is *CollectionObservatory*, a comprehensive tool to detect data collection and web tracking. CollectionObservatory is valuable both as a user awareness tool itself (to help inform users about third-party content on the webpages they visit collecting information about their browsing behaviors) as well as to support our other user awareness tools, such as AdObservatory and DiscriminationObservatory. For example, AdObservatory will leverage CollectionObservatory to identify those trackers that collect and use users' information to target ads at them. In prior work we developed a more limited browser-based web tracking detection and measurement platform which detects only cookie-based tracking [60, 63]. CollectionObservatory will build upon our experience but move significantly beyond it to (1) detect web tracking behaviors of much more diverse and subtle types and (2) provide effective user-facing visualizations of the observed behaviors. The key contributions in CollectionObservatory will thus be:

Comprehensive web tracking detection. Our previous work, TrackingObserver [63], detects primarily cookie-based tracking that explicitly store state in the user's browser. In CollectionObservatory, we will extend the scope of this automatic detection to include additional tracking behaviors, including *fingerprint-based trackers* and more esoteric tracking mechanisms (e.g., cache-based, Flash cookies, etc. [39]). Fingerprinting-based trackers re-identify users based on unique combinations of attributes such as IP address, user agent, installed fonts and plugins, etc [22]. While researchers have explored how fingerprinting works and conducted limited measurement studies of specific fingerprinting techniques or known fingerprinting libraries (e.g., [2, 3, 55, 73]), there has been no extensive non-blacklist-based study of fingerprinting in the wild nor a user-facing tool to detect these behaviors. Implementing fingerprint-based tracking detection in CollectionObservatory, e.g., via hooks on the JavaScript APIs commonly used to generate fingerprints, would allow us to perform a similar study for these trackers. We will conduct a measurement study of tracking on a large number of popular and less popular websites, including from different vantage points (e.g., from different geographic locations). Ultimately, these findings will inform a user awareness tool for web tracking, described below.

Effective visualizations of third-party web content. Several tools exist to reveal which third-party trackers are loaded on a given web page, but (as described above) none of these tools localize those trackers on the page. That is, a user can learn that `doubleclick.net` was contacted as the page was loaded, but not which, if any, ads on the page were served by `doubleclick.net`. Similarly, a user cannot easily answer "where did this ad come from?" for a given ad, since even ads loaded from a particular domain may have been placed there by a different third-party (typically an advertising network) [60]. Indeed, some ads might even be unintended by the web page developer, such as those injected by malicious browser extensions `http://ars.to/1mgzNbt`. We propose a tool to identify third-party content on a page and attribute it to its source; achieving this requires addressing a number of technical challenges, including identifying content modifications on the first-party page that result from third-party scripts. We plan to integrate this tool with CollectionObservatory, and envision that it can be used to bootstrap both a user study of attitudes towards and expectations surrounding web tracking (see Section 4.3) as well as a measurement study of third-party content on the web.

Full-fledged web tracking transparency tool. Building on the above and on other aspects of the Hubble infrastructure, and informed by the user studies we describe in Section 4.3, we will ultimately extend CollectionObservatory into a full-fledged web tracking transparency tool for end users. In addition to providing useful visualizations to users about how their information is collected and used as they browse the web, this tool will provide useful, actionable, and verifiable changes that users can make to improve their privacy. We will release this final version of CollectionObservatory as open source, and we will deploy the tool publicly, ideally as part of an existing tool (e.g., EFF's Privacy Badger), as we have done with ShareMeNot [62]). This deployment will serve as a field study of the tool, which in turn will inform additional iteration on the tool itself.

4.2.4 LocationObservatory: Revealing Privacy Implications of Location Tracking

Our fourth tool extends our analysis in an emerging new direction: the use of geo-located data records for personalization, already reported as a growing trend [10, 53]. Location data are especially revealing as it connects to the offline world, and was historically used before the Internet for discriminatory practice. In fact, ensuring privacy against those forms of personalization has been a very active area [33, 54]. Yet, location-based personalization has rarely been quantified.

We propose *LocationObservatory*, whose goal is to detect which current or past location information are responsible for a differentiated treatment in ads shown on a mobile device. It leverages Hubble especially through an experiment design exploiting the multi-resolution nature of location information (state $\rightarrow$ city $\rightarrow$ neighborhood $\rightarrow$ venue) to conduct a chain of experiments with finer and finer granularity. We also suspect that ageing of offline location data in personalization have a very different nature than online, and address that point separately. It also poses unique challenges that LocationObservatory addresses: while a basic use of Hubble generates inputs to test at random, we will augment Hubble to account for constraints that satisfies law of human travels, using rejection and importance sampling. Lastly, location data has a rich semantics, and new data visualization tools are needed when results are presented to users (see § 4.3).

4.3 Thrust 3: User Studies and Transparency Tool Measurements

To maximize the effectiveness of the transparency infrastructure and the user awareness tools that we build, it is critical that we understand users themselves. To this end, our proposed work will include user studies of two types: (1) user studies to help us understand *users' existing mental models and attitudes*, and (2) user studies to help us *evaluate the effects of our tools*. We will work with our institutions' human subject review boards to obtain IRB approval before conducting any studies involving human subjects. In fact, to date, PIs Roesner and Chaintreau already conducted research on topics related to this effort (human attitude to privacy, and markets for personal information) and securing multiple times approval of their protocol from IRBs.

User Studies for Existing User Mental Models and Attitudes. Our transparency and user awareness tools aim to close the gap between users' existing mental models and attitudes with respect to the privacy of their data and the reality of what today's applications and services collect and use. To achieve this, we must first understand what users already know or believe about the collection and use of their private data. Prior work has studied users' mental models and attitudes in contexts such as targeted advertising (e.g., [44, 47, 57, 68]); we propose to extend that work here, and to update the findings for current users and systems.

Example: Reactions to Ad Targeting. As one example, we detail a user study to help inform our transparency and user awareness tools for web tracking and targeted advertising. We ask: what are users' mental models about ad targeting? How will they react upon learning that a particular ad is targeted at them? To explore this question, we will initially design a study in which we post ads (e.g., via Facebook or Google) targeted at specific—possibly sensitive—keywords. The content of our ads will inform the person viewing them about the targeting, e.g., by revealing the keyword that was used to target that particular ad. Clicking on the ad will direct participants to a page with additional information about targeted advertising and about our study, including survey questions to help us evaluate the participants' reactions to (1) learning about the targeting as well as to (2) the targeting itself. As a second part of this study, we will conduct a user study with our AdObservatory tool to study users' reactions to real targeting that they encounter in the wild.

By evaluating and comparing participants' reactions to different targeting keywords, our results can help motivate and inform our transparency tools, which may in turn motivate changes within targeting systems themselves. For example, if we find that users are comfortable with ads targeted at debt-related keywords but not cancer-related keywords, we might recommend that ad targeting companies stop targeting cancer, or offer an opt-in to such "sensitive" topics. More broadly, studies such as this one will help us understand the notion of "sensitivity" — how much does it depend on the user, what kinds of things are uniformly "sensitive," etc.? These findings will ultimately inform our transparency and user awareness tools as well as others working in this space.

User Studies to Evaluate our Tools. In addition to user studies aimed to teach us about users in general, we must also evaluate the effectiveness of our tools – AdObservatory, DiscriminationObservatory, CollectionObservatory, and LocationObservatory– with real users. Our goals here include (1) validating that the information our tools surface to users is comprehensible, (2) studying immediate user attitudes and reactions to learning this information, and (3) observing and tracking sustained user behavior changes (or lack thereof) in response to learning this information.

These studies will take several forms throughout the design of each tool, beginning with limited usability studies of preliminary designs, followed by more in-depth studies to evaluate the effectiveness of our tools to improve user comprehension and to positively affect user behaviors, culminating in full-fledged beta-tests with real user populations. For example, co-PI Roesner has previously released a user-facing anti-web tracking tool (originally called ShareMeNot [62]) as part of the Electronic Frontier Foundation's Privacy Badger tool. We will use connections like these to iteratively beta-test our tools with large numbers of real users in real contexts.

5 Personnel and Management Plan

The team members are faculty at two institutions: Columbia University and University of Washington. Columbia University will be the Prime Contractor for the project, with University of Washington acting as a subcontractor; the formal agreements are already in place for this project. Roxana Geambasu will be the overall project PI, responsible for general technical direction, coordination and reporting (in addition to conducting a portion of the research). Each co-PI will be responsible for one or more component and associated sub-tasks (see Fig. 4). Each faculty member will be responsible for supervising Ph.D. Graduate Research Assistants (GRAs) and will dedicate a significant amount of his/her own time to this project (see Fig. 3).

Key Individual	2015	2016	2017	2018	2019
Geambasu	53 h	160 h	160 h	160 h	160 h
Chaintreau	53 h	160 h	160 h	160 h	160 h
Hsu	53 h	160 h	160 h	160 h	160 h
Roesner	53 h	160 h	160 h	160 h	160 h

Fig. 3: **Team member commitments.**

The management structure is relatively flat, with Geambasu the lead PI and everyone else working with each other and under the general guidance of Geambasu. The PIs already have a history of collaboration with each other and are co-advising students. For example, Chaintreau and Geambasu co-authored the XRay paper [43] and are co-advising a Ph.D. student, the paper's first author.

Component	Sub-tasks	Responsible PI(s)
Hubble infrastructure	1.1, 2.1, 3.1	Geambasu
Statistical correlation and causation	1.3, 1.4, 2.3, 2.4, 3.3, 3.4	Hsu
Privacy-preserving transparency	1.5, 2.5, 3.5	Chaintreau
CollectionObservatory	1.7, 2.7, 3.7	Roesner
AdObservatory	1.2, 2.2	Geambasu
DiscriminationObservatory	2.2, 3.2	Geambasu
LocationObservatory	1.6, 2.6, 3.6	Chaintreau
User studies	1.8, 2.8, 3.2, 3.6, 3.8	Roesner, Chaintreau, Geambasu
Integration, Evaluation on TA3	1.9, 2.9, 3.9	All PIs

Fig. 4: **Team member responsibilities (research areas and subtasks).**

Chaintreau, Geambasu, and Hsu have been working on follow-on technology and are now writing a joint paper for CCS'15 on a related topic. Geambasu and Roesner have already started a collaboration in the space of user awareness studies. The Columbia Co-PIs meet face-to-face almost on a daily basis. To facilitate collaboration with the UW Co-PI, we will have regular meetings over Skype or other technology, as well as two physical meetings per year. We will use a wiki and Github for coordination and record keeping. **All code will be made public on Github.**

5.1 Personnel Bios

The PIs span a broad range of expertise: *systems* (Geambasu), *theory and social networks* (Chaintreau), and *machine learning and statistics* (Hsu), and *security and human factors* (Roesner).

Roxana Geambasu is an Assistant Professor of Computer Science at Columbia University. She has made research contributions in software systems, including operating systems, distributed systems, and security and privacy. One over-arching theme relates to increasing privacy in today's data-driven world by developing transparency, fairness, and data management tools for programmers, privacy watchdogs, and end-users. Publications at: `www.cs.columbia.edu/~roxana`. Geambasu is a member of the Information Science and Technology (ISAT) focus group. For her work in privacy, Geambasu received a Microsoft Research Faculty, a Popular Science "Brilliant 10" listing, an Honorable Mention for the inaugural Dennis M. Ritchie Doctoral Dissertation Award, a William Chan Dissertation Award, two best paper awards at top systems conferences (USENIX Security and EuroSys), and the first Google Ph.D. Fellowship in Cloud Computing. Geambasu's research was featured in multiple articles in New York Times, The Economist, NPR.

Augustin Chaintreau is an Assistant Professor of Computer Science at Columbia University since 2010, where he directs the Mobile Social Lab. He designs algorithms leveraging social mobile behaviors or incentives, to reconcile the risk and value of personal data networking. His research addressing transparency in personalization, fairness in personal data markets, efficiency in social information sharing, cross domain data linkage, and human mobility lead to 25 papers in tier-1 conferences (five receiving best paper awards at ACM CoNEXT, SIGMETRICS, USENIX IMC, IEEE MASS, Algotel, some with media coverage such as the NYT blog). In 2013, he received the NSF CAREER and ACM SIGMETRICS Rising star award, was PC chair of ACM CoNEXT, and members of 28 tier-1 conference PCs from ACM, IEEE and AAAI.

Daniel Hsu is an Assistant Professor of Computer Science at Columbia University, and is a member of the Data Science Institute, also at Columbia. His research interests are in algorithmic statistics, machine learning, and privacy-preserving data analysis. His work on interactive and unsupervised learning have yielded the first computationally efficient and statistically consistent algorithms for a number of core estimation and learning problems that were only previously tackled using heuristics or suboptimal methods. Much of his current research focuses on developing scalable and statistically sound learning algorithms for discovering hidden structure in massive data, as well as on the interaction between statistical inference and privacy. He was the organizer of several workshops and tutorials on algorithms for learning hidden variable models at premier machine learning venues (ICML, NIPS); he received a Yahoo Academic Career Enhancement Award in 2014 and the UC San Diego Departmental Dissertation Award in 2010.

Franziska Roesner is an Assistant Professor of Computer Science & Engineering at the University of Washington. She has made research contributions in computer security and privacy, spanning broadly from systems to human factors. A list of her publications is available at: `http://www.franziroesner.com`. Her work on web privacy included the development of ShareMeNot, a defense for one type of web tracker, which was incorporated into the Electronic Frontier Foundation's Privacy Badger tool in 2014. For her work in security and privacy, Prof. Roesner received the William Chan Memorial Dissertation Award in 2014, the IEEE Symposium on Security and Privacy Best Practical Paper Award in 2012, a NSF Graduate Research Fellowship, and a Microsoft Research PhD Fellowship.

5.2 Integration and Evaluation

Although each component is led by a particular team member, the PIs will work together as part of a unified team to integrate their components in a coherent system and a useful suite of tools. The end product will be a robust infrastructure that can be leveraged by other researchers and developers to reveal other aspects of personal data treatment on the web. The infrastructure can be used to audit TA3 systems that rely on personal information; these systems will expose the types of personal data that are used as input (e.g., user browsing data, e-mails), and what kinds of measurable outputs the system will produce (e.g., ad placement decisions). Our tools will provide a means to inform users of the privacy implications of using or interacting with such systems.

We will conduct a thorough evaluation of our infrastructure prototype and tools using well-established evaluation metrics and methods. We will assess the scalability of our system as the number of possible targeting inputs and outputs grows. We will also assess the precision and recall of our system in detecting known targeting behavior in systems where ground-truth has been established. As already discussed in §4.3, the user-facing transparency tools will be thoroughly evaluated in comprehensive user studies.

6 Capabilities

PI Geambasu has been working on increasing privacy and transparency in computer systems for multiple years. As part of a DARPA MRC project (MEERKATS), she has CleanOS, a mobile operating system designed with privacy and transparency in mind [64, 65], which manages users' data carefully so as to minimize its exposure to attacks and provide auditing of exactly what data was exposed following an attack. Geambasu and Chaintreau have recently developed *XRay*, a preliminary transparency infrastructure that reveals data targeting in Web services [43]. The system was the first to accurately reverse targeting in multiple services, including Gmail, Amazon, Youtube. However, it is limited in scale, applicability, and features – limitations that Hubble will address. Finally, Geambasu has a track record of transition into practice of the systems she builds [27, 69]. For example, Synapse [69], a scalable, heterogeneous-database replication system, has been deployed at Crowdtap, a data-driven marketing startup in NYC, which has been running it in production for about a year with great success.

PI Chaintreau produced research addressing the need for better fairness and transparency in personalization. In addition to the XRay system already mentioned above, with Telefonica and AT&T, he proposed a solution based on pseudonyms and auctions to redistribute economic value of web-browsing to the users [58], and reveal the revenue made available to online advertising through tracking [29]. These results, along with new techniques to increase the transparency of online services, propose concrete steps to reconcile privacy and the deployment of big data.

PI Hsu works on algorithmic statistics, machine learning, and privacy-preserving data analysis. He has developed several foundational algorithms in the areas of active learning and unsupervised learning. His work on noise-tolerant and statistical active learning (e.g., [8, 17]) provides the algorithmic basis for adaptive experimental design in classification problems, which we hope to employ in Hubble for scalability. His work on efficient algorithms for learning latent variable models (e.g., [7,37]) provides techniques for capturing hidden structure in data, which can be used to improve the statistical power for finding significant correlations and causal relationships. Additionally, Hsu has studied implications of privacy constraints on statistical data analysis [13], and has experience in developing scalable learning algorithms for complex regression problems [36].

PI Roesner has worked on web privacy topics for several years. Her taxonomy and measurements of third-party web tracking in the wild [60] was among the first efforts to deeply understand the web tracking space. As part of this work, Roesner developed *ShareMeNot*, a defense for social media web trackers (such as the Facebook "Like" button). ShareMeNot's techniques were adopted by Ghosteryand its code was incorporated into the EFF's Privacy Badger (`eff.org/privacybadger`) web privacy tool. Roesner also worked on ensuring that privacy properties of systems match users' expectations in other contexts (e.g., [59, 61]).

7 Statement of Work

Our effort is composed of one overall task, aimed at developing a complete and demonstrable Hubble prototype and tools. We split this task below in multiple per-phase tasks.

7.1 Phase 1 (Months 1-18)

TASK 1.1: **Objective**: Design and implement basic Hubble infrastructure and tool development API.
General Description: Design early version of Hubble's architecture and developer APIs. The architecture will support single-stage experiments (no reactive). Focus on controlled-input use cases.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Infrastructure that reveals input/output targeting by measuring correlation on differentiated profiles. Supports 100s of inputs and has precision/recall for detecting targeting of 70-90%.
Deliverables: Early software prototype and design documents.

TASK 1.2: **Objective**: Design and implement basic AdObserver tool.
General Description: Implement a basic version of the AdObserver tool to exercise Hubble's architecture and APIs.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Tool reveals ads targeted on previously visited websites.
Deliverables: Software prototype and design documents.

TASK 1.3: **Objective**: Develop basic statistical methodology for testing targeting hypotheses.
General Description: Develop a formal specification for targeting hypotheses as generated by Hubble, plus a methodology for reliable testing of the hypotheses.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Specification of targeting hypotheses and basic statistical engine.
Deliverables: Software prototype and design documents.

TASK 1.4: **Objective**: Apply scalable sparse linear regression methods to generation of targeting hypotheses.
General Description: Develop sparse linear regression approach to infer putative targeting hypotheses from observations. Evaluate scalability using simulated targeting mechanisms.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Scalable and empirically-validated implementation, incorporated into Hubble pipeline.
Deliverables: Software prototype and design documents.

TASK 1.5: **Objective**: Design and implement basic privacy-preserving transparency protocol.
General Description: Design a protocol leveraging privacy preserving statistical queries (generic baseline + `aircloak`); scale target is 10s-100s inputs; compare precision/recall to custom-made solution.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: A transparency mechanism on statistical queries, with accuracy comparable to custom-made solution.
Deliverables: Software prototype, design documents, performance evaluation.

TASK 1.6: **Objective**: Design and implement basic LocationObserver to reveal what can be inferred from location.
General Description: Tools that reveal geographical targeting and provide interpretative context through maps correlated with multiple demographics (no privacy support).
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Transparency tool with 70%-90% precision-recall, presented with ethnic balance in metropolitan areas.
Deliverables: Software, design documents, preliminary conclusions of user study.

TASK 1.7: **Objective**: Implement fingerprint tracking detection infrastructure in CollectionObservatory.
General Description: Implement detection of fingerprint-based web trackers that use browser and machine fingerprinting techniques to re-identify users. Uee entropy from a potential tracker's JavaScript API accesses.
Responsible Organization and Location: University of Washington (Seattle, WA)
Exit Criteria: Initial version of CollectionObservatory that successfully detects a large fraction of fingerprint-based trackers, evaluated by a comparison with blacklist-based tracking detection tools.
Deliverables: Initial version of CollectionObservatory that detects fingerprint-based trackers.

TASK 1.8: **Objective**: Conduct user study of attitudes towards targeting.
General Description: Conduct a user study to better understand users' attitudes towards targeted advertising. Target ads using a variety of keywords (including sensitive keywords) and inform users about the targeting in the content of the ads. For participants who click on the ad, debrief them about the study and ask addition survey questions.
Responsible Organization and Location: University of Washington (Seattle, WA)
Exit Criteria: Sufficient participation in the user study to draw statistically significant conclusions.
Deliverables: Conclusions drawn from user study results.

TASK 1.9: **Objective**: Demonstrate our TA2 technology on a TA3 Research System.
General Description: Integrate basic Hubble and transparency tools with TA3 Research System(s).
Responsible Organization and Location: Columbia University (New York), University of Washington (Seattle)
Exit Criteria: Successful detection of data use in TA3 Research System.
Deliverables: Software prototypes, design documents, and results from evaluation.

7.2 Phase 2 (Months 19-36)

TASK 2.1: **Objective**: Extend Hubble and APIs for multi-stage transparency tool designs.
General Description: Incorporate support for multi-stage transparency tools (validation, attribution). Incorporate causal inference building block as part of the validation.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: A system capable of validating and explaining its own causal targeting hypotheses. Scale will be in the range of 100s-1000s inputs, but we expect its recall/precision to grow thanks to validations.
Deliverables: Software prototype and design documents.

TASK 2.2: **Objective**: Extend AdObserver and DiscriminationObserver to leverage Hubble's multi-stage architecture.
General Description: Design and implement using Hubble's APIs validation and refinement stages for each tool. Run experiments to test and evaluate.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Tools that both scale and validate/explain their own assessments to the users.
Deliverables: Software prototype and design documents.

TASK 2.3: **Objective**: Develop methodology for generating and testing targeting hypotheses from observational data.
General Description: Explore and evaluate techniques for estimating causal or correlation effects from observational based on an assumed casual model.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Software tool for hypothesis generation and testing using observational data.
Deliverables: Software prototype and design documents.

TASK 2.4: **Objective**: Extend sparse linear regression methodology to support complex targeting hypotheses.
General Description: Develop multi-stage methodology to support testing of complex targeting hypotheses with higher-order input interactions. Evaluate this strategy using simulated data and real data collected by Hubble.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Scalable and empirically-validated implementation linear regression approach using higher-order inputs, incorporated into Hubble pipeline.
Deliverables: Software prototype and design documents.

TASK 2.5: **Objective**: Extend privacy-preserving transparency to avoid trust in a central point.
General Description: Scale design by refining statistical queries using data constraints, grouping, and preprocessing exploiting low dimensionality.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: A privacy preserving procotol that regain accuracy for up to 1,000 inputs.
Deliverables: Software prototype and design documents.

TASK 2.6: **Objective**: Extend LocationObserver to integrate privacy-preserving techniques.
General Description: Integrate basic privacy preserving techniques with LocationObservatory, to operate with on range of 10-100 locations. Conduct first experiment with real user data.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: A privacy preserving tracker of location data usage used by 10 participants for a month.
Deliverables: Software prototype, design documents, conclusion from user study.

TASK 2.7: **Objective**: Measurement study with CollectionObservatory.
General Description: Using fingerprint-based tracking detector in CollectionObservatory (as well as existing capabilities in TrackingObserver from prior work), conduct large-scale measurement study of tracking on the web.
Responsible Organization and Location: University of Washington (Seattle, WA)
Exit Criteria: Measurement study of tracking on many websites from multiple vantage points (e.g., geo locations).
Deliverables: Measurement study results, source code.

TASK 2.8: **Objective**: Small-scope user awareness tool that visualizes third-party content.
General Description: Develop an initial user awareness tool for web tracking that identifies third-party content on a webpage and visualizes it for the user. This tool, combined with CollectionObservatory, will serve as a building block for our later, more full-fledged web tracking user awareness tool.
Responsible Organization and Location: University of Washington (Seattle, WA)
Exit Criteria: Software prototype that identifies and visualized third-party content on a webpage.
Deliverables: Software prototype and design documents.

TASK 2.9: **Objective**: Demonstrate our enhanced TA2 technology on a TA3 Research System. Initial trial of demonstration on a TA3 Existing System.
General Description: Integrate enhanced implementation of Hubble and transparency tools with the Research System(s) implemented by TA3 researchers. Begin integration of our tools with Ta3 Existing System(s), as well as TA1 and TA2 protection-oriented technologies to enable auditing of the effectiveness of their protection.
Responsible Organization and Location: Columbia University (New York), University of Washington (Seattle)
Exit Criteria: Successful detection of data use in TA3 Research System.
Deliverables: Software prototypes, design documents, and results from evaluation.

7.3 Phase 3 (Months 37-54)

TASK 3.1: **Objective**: Extend Hubble to support collaborative transparency scenarios.
General Description: Incorporate statistical correlation building block for uncontrolled inputs to support end-user scenarios. Also incorporate privacy-preserving protocols to limit the need for users to trust Hubble. Run experiments with simulated users to evaluate.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: A privacy-preserving collaborative transparency system where users can submit their inputs/outputs partially and retrieve targeting assessments.
Deliverables: Software prototype and design documents.

TASK 3.2: **Objective**: Extend AdObserver, DiscriminationObserver to the collaborative use case.
General Description: Port the tools to the collaborative version of Hubble and re-run measurements in a simulated collaborative scenario for evaluation.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Transparency tools now run on observational data of the end users without the need to trust Hubble.
Deliverables: Software prototype and design documents.

TASK 3.3: **Objective**: Develop and evaluate statistical testing methodology for stratification structure.
General Description: Develop methods for discovering latent population stratification (clustering), together with hypothesis tests that leverage this stratification structure to increase the statistical power to detect targeting.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Software tool for computation of statistical tests.
Deliverables: Software prototype and design documents.

TASK 3.4: **Objective**: Extend sparse linear regression techniques to use adaptive multi-stage experimental designs, and incorporate statistical testing methods to generate higher-order targeting hypotheses.
General Description: Develop multi-stage methodology for exploiting groups of related targeting inputs and outputs. The group structures are inferred in a first experimental stage, and the subsequently exploited in a second stage using group-sparse linear regression methods to discover group-level targeting hypotheses.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Scalable and empirically-validated implementation of multi-stage group-sparse linear regression approach, incorporated into Hubble pipeline.
Deliverables: Software prototype and design documents.

TASK 3.5: **Objective**: Finalize privacy-preserving, collaborative transparency building blocks and integrate in Hubble.
General Description: Sustain scaling with higher accuracy by exploiting structure (spatio-temporal data, topical), and multi-stage statistical query logic.
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Scale up transparency to multi-resolution inputs (10,000 at finer grain), under comparable accuracy/privacy performance guarantees as previously observed.
Deliverables: Software prototype, design documents, and performance evaluation.

TASK 3.6: **Objective**: Finalize LocationObserver tool and run studies of impact of transparency on user actions.
General Description: Scale privacy preserving location data usage tracker using multi-stage and stuctures in statistical queries; conduct a longitudinal study on impact on privacy awareness
Responsible Organization and Location: Columbia University (NYC)
Exit Criteria: Tool that scale up to zipcode at state/national level. Recommendations on user awareness tool grounded on longitudinal results.
Deliverables: Software Prototype, results from experiments, user study conclusion on effect of awareness.

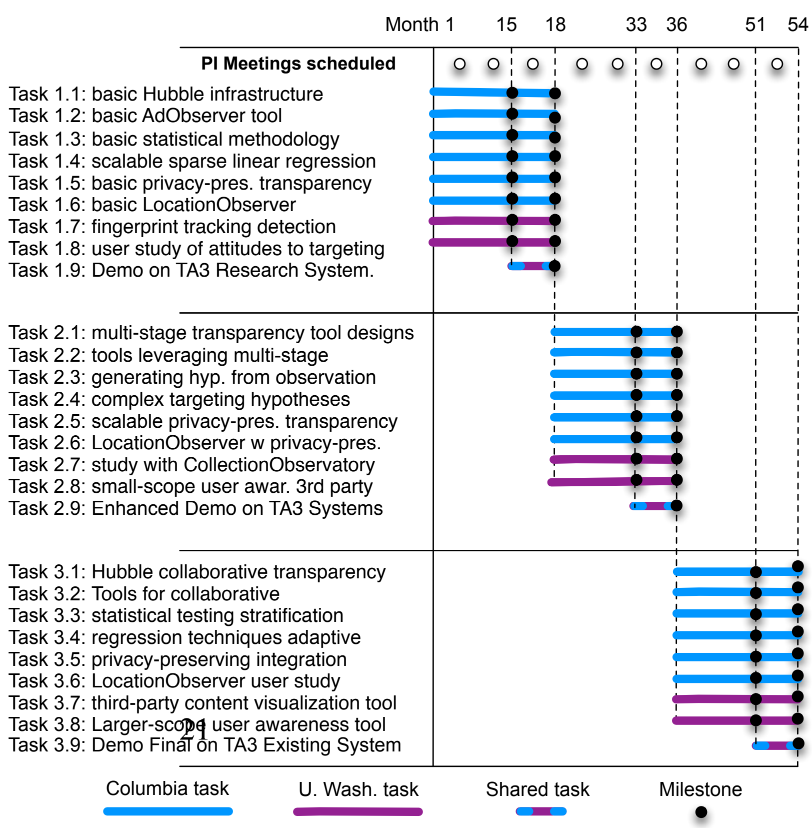
TASK 3.7: **Objective**: User study of third-party content visualization tool.
General Description: We will conduct a usability study of the previously developed third-party content visualization tool, to understand whether and how the tool is effective with real users: does it effectively convey information to users? Do users take useful actions in response to this information? etc.
Responsible Organization and Location: University of Washington (Seattle, WA)
Exit Criteria: Conduct user study with a sufficient number of participants to generate statistically significant results and inform interactive improvements to the tool.
Deliverables: User study results and iterative improvements to the software prototype.

TASK 3.8: **Objective**: Larger-scope web privacy user awareness tool.
General Description: Develop a more full-fledged web tracking user awareness tool, integrating functionality from the previously developed third-party content visualization tool and from CollectionObservatory.
Responsible Organization and Location: University of Washington (Seattle, WA)
Exit Criteria: Develop a more full-fledged web tracking user awareness tool informed by and building on other aspects of the project.
Deliverables: Software prototype and design documents.

TASK 3.9: **Objective**: Demonstrate our final TA2 technology on TA3 Research and Existing Systems.
General Description: Integrate final implementation of Hubble and transparency tools with the Research and Existing Systems implemented by TA3 researchers. Integrate our tools with some TA1 and TA2 protection technologies to enable auditing of their effectiveness.
Responsible Organization and Location: Columbia University (New York), University of Washington (Seattle)
Exit Criteria: Successful detection of data use in TA3 Research and Existing Systems. Successful auditing of effectiveness of other TA1, TA2 technologies.
Deliverables: Software prototypes, design documents, and results from evaluation.

8 Schedule and Milestones

The Gantt chart to the right provides a graphic representation of the project schedule at the level of sub-tasks, all of which fall with the one overall task of Hubble, aimed at developing a complete and demonstrable Hubble prototype and tools. Program milestones are indicated via bullets. Tasks are colored by responsible institution. Some tasks are joint, and they have a mixed color. We only show the major milestones of the program. All tasks except integration/evaluation additionally have a milestone to de-



liver working prototypes before the integration/evaluation tasks (Tasks 1.9, 2.9, 3.9) begin.

9 Cost Summary

Entire Performance Period (Total: $3,960,419)

	Columbia University (CU) (prime)	University of Washington (UW) (sub)	Category Total
Direct Labor	1,270,820	402,258	1,673,078
Materials ODC	783,786	324,082	1,107,868
Indirect Costs	910,322	269,151	1,179,473
Member Totals	2,964,928	995,491	3,960,419

GFY 15 (Total: $104,438)

	CU (prime)	UW (sub)	Total
Direct Labor	23,921	7,844	31,765
Materials	1,517	1,196	2,713
ODC	18,594	12,725	31,319
Indirect Costs	32,962	5,679	38,641
Member Totals	76,994	27,444	104,438

GFY 16 (Total: $885,835)

	CU (prime)	UW (sub)	Total
Direct Labor	297,808	94,277	382,085
Materials	39,200	12,855	52,055
ODC	142,269	42,071	184,340
Indirect Costs	205,205	62,148	267,353
Member Totals	674,481	211,351	885,832

GFY 17 (Total: $923,294)

	CU (prime)	UW (sub)	Total
Direct Labor	296,940	96,167	393,107
Materials	39,200	12,930	52,130
ODC	146,087	58,067	204,154
Indirect Costs	210,684	63,219	273,903
Member Totals	692,911	230,383	923,294

GFY 18 (Total: $949,555)

	CU (prime)	UW (sub)	Total
Direct Labor	306,367	97,493	403,860
Materials	39,200	12,984	52,184
ODC	150,019	63,182	213,201
Indirect Costs	216,340	63,970	280,310
Member Totals	711,926	237,629	949,555

GFY 19 (Total: $898,226)

	CU (prime)	UW (sub)	Total
Direct Labor	294,556	86,783	381,339
Materials	31,683	12,209	43,892
ODC	141,732	68,808	210,540
Indirect Costs	204,745	57,711	262,455
Member Totals	672,716	225,510	898,226

GFY 20 (Total: $199,074)

	CU (prime)	UW (sub)	Total
Direct Labor	61,228	19,694	80,922
Materials	0	4,926	4,926
ODC	34,285	22,130	56,415
Indirect Costs	40,387	16,424	56,811
Member Totals	135,900	63,174	199,074

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10 Appendix A

10.1 Team Member Identification

Individual Name	Role (Prime, Subcontractor or Consultant	Organization	Non-US?		FFRDC or Govt?
			Org.	Ind.	
Geambasu	Prime	Columbia University	N/A	N/A	N/A
Chaintreau	Prime	Columbia University	N/A	N/A	N/A
Hsu	Prime	Columbia University	N/A	N/A	N/A
Roesner	Subcontractor	University of Washington	N/A	N/A	N/A

10.2 Government or FFRDC Team Member Proof of Eligibility to Propose

NONE

10.3 Government or FFDRC Team Member Statement of Unique Capability

NONE

10.4 Organizational Conflict of Interest Affirmations and Disclosure

NONE

10.5 Intellectual Property (IP)

The Offeror and subcontractors reserve the right to independently or jointly seek intellectual protection for the results of the work under this program. These rights will not compromise the values of the proposed work to the Government because it will have access to and use of the research and results of this work.

10.6 Human Subjects Research (HSR)

The proposed work includes user studies that will involve human subject research. The proposed studies will be designed and conducted according to procedures approved by the organizations' Institutional Review Boards (IRBs). Ample time will be allotted to complete the approval process for each study.

10.7 Animal Use

NONE

10.8 Representations Regarding Unpaid Delinquent Tax Liability or a Felony Conviction under Any Federal Law

(a) The proposer represents that it is [ ] is not [**X**] a corporation that has any unpaid Federal tax liability that has been assessed, for which all judicial and administrative remedies have been exhausted or have lapsed, and that is not being paid in a timely manner pursuant to an agreement with the authority responsible for collecting the tax liability.
(b) The proposer represents that it is [ ] is not [**X**] a corporation that was convicted of a felony criminal violation under a Federal law within the preceding 24 months.

10.9 Cost Accounting Standards (CAS) Notices and Certification

NONE