1 Big Data and User Valuation: a Synergistic Combination

Big data analytics is the problem of bringing the massive amounts of data produced today down to human scale. This problem is faced by scientists, engineers, physicians, and many others in knowledge-intensive professions, when dealing with repositories that collect the data and the results in their fields. To address this problem, this project will develop novel algorithms and open-source infrastructure for improving discovery and access to repositories. These algorithms will aggregate and analyze the usage patterns and explicit valuations (social analytics) that professional communities provide.

Diverse human minds interacting with data collections, as they carry out their own research or operational activities, provide an immensely powerful source of information. Methods for aggregating, organizing and evaluating interactions between users and data can elucidate previously invisible structure within data collections, accelerating the processes of scientific discovery. Users who interact with data and share valuations of items and sets of items reveal more about their own interests, making it possible to discover relations among items in a shared repository. While some scientific disciplines have been slow to move towards data sharing, others (e.g., astrophysics) have transformed their research cultures in a few decades of data coordination and sharing.

The team of researchers, from Rutgers, Cornell, and Princeton, have been working closely together to develop personalized recommendation systems for the arXiv\(^1\), one of the oldest and most influential online collections of scientific articles. The arXiv, created by co-PI Paul Ginsparg, and now housed at the Cornell University Library, contains over 750,000 e-prints in Physics, Mathematics, Computer Science, Quantitative Biology, Quantitative Finance, and Statistics. The arXiv has a collection of 1.5 billion user accesses, and each month has over 16 million user accesses and over 7,000 new articles submitted. Elucidating hidden structure in the arXiv from user behavior will require fundamental advances in big data analytics.

Figure 1 summarizes our proposed system. We use the features of the texts in the collection, and user data to induce and track representations of the articles and of the users. These representations support estimates about how each user would value specific articles and, ultimately, sets of articles. We use these predictions to recommend diverse sets of articles to each user.

Our system must be a “life-long learner” and our proposed algorithms are designed to operate sequentially. New articles appear daily and are folded into the system; new user data arise when users interact with our recommendations and with our valuation interface. Further, we are developing new ideas that balance learning more about a user with presenting articles that she is already expected to value. Finally, we will use rigorous formative evaluation to guide the development and combination of the several components as we learn more about how the components work together.

This paradigm is broadly applicable. Other online services, such as the start-up Mendeley.com and the Computer Science Repository CiteSeer, will immediately be able to use the software and algorithms that we will produce. Furthermore, the resulting ideas and algorithms are not restricted to professional scientists—our system can be ported to recommending new medical results to physicians or intelligence reports to

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\(^1\)http://www.arXiv.org/ (pronounced “archive”)
analysts. In this framework, personalized recommendation is seen not only as an added value to the users, but as a way of learning more about both data and users, by tracking how the data is used.

Conventional methods for accessing and organizing scientific collections, such as citation analysis, posit a global notion of importance. This leads to several problems. According to the “Matthew Effect” [101, 121, 30, 65], even if all articles posted on a given day were “equally important,” the state in which they are equally cited is unstable: a distribution similar to the observed distribution of citations would arise even without differences in merit. In addition, stratagems such as submitting an article moments after the daily 16:00 EST cutoff can give a measurable boost to the number of citations that an article attracts [51]. These problems are also addressed by the recommendation function.

Synergies and Valuations. Very broadly, one may say that data elements may be related to each other in pair-wise fashion (usually thought of as a similarity, $Sim(d, d')$) or in set-wise fashion (which we express notionally in terms of a set function $Syn(D)$, where $D$ is a set of data elements). To say that a set of data elements $D = \{d_1, d_2, ..., d_K\}$ has high $Syn$-value is to assert that research that benefits from seeing some of the elements in the set would benefit super-linearly from discovering additional elements in the set. This is in contrast to the linear relation that exists if the set does not exhibit such synergies (hence the name $Syn$).

The Role and Scope of Recommendation. Such relations among data elements can only be discovered if the algorithms computing $Syn(D)$ are “aware” of the nature of the synergies. Human users of the data can accelerate our development of such algorithms if we can capture some part of human judgment in a complementary set function representing the (person-dependent) valuation function, $U(u, D)$. Thus, if $U(u, D)$ is increased, when person $u$ indicates that it is valuable to consider the elements of $D$ together, that fact can be incorporated into algorithmic development in several ways. Such a scheme depends crucially on motivating the data users to share this information. We propose to provide that motivation by using the elicited information to significantly improve a recommendation function.

As users browse and/or read articles, the system can recommend articles based on what they have read, how they value it, what others similar to them have read, and the contents (i.e., features and topics) of the articles.
The system may recommend older articles that others have read, and new articles that have not yet been read by anyone. Profiles, structures and recommendations can change and drift; users’ interests change over time; new articles appear every day; and our collective knowledge grows in new ways. All of this must operate at scale: there are hundreds of thousands of articles and tens of thousands of users. Our recommendations must exploit this data stream, while working on a cluster of servers.

2 BIGDATA Capacity Building

The proposed research most directly addresses the third specific aspect of capacity building: sustainable, cost-effective infrastructure for data storage, access and shared services. Our contribution is to software, rather than hardware, and we propose to develop reusable and open-source software that can be applied to other similar collections. We believe that the underlying concepts will also be translatable in two distinct ways to other kinds of collections. The first mode of translation is to use associated text to improve access to and coordination of the data in enormous sets. Examples that are already in use commercially are the “nearby texts” that are used to produce impressive (if sometimes amusing) retrieval of images from the World Wide Web. Association of texts with research images, such as fMRI data sets is a more challenging example. The second mode of translation to other kinds of Big Data would require that researchers find the appropriate formulations of the $\text{Syn}(D)$ and $\mathcal{U}(u, D)$ for very different collections such as medical laboratory reports, intelligence reports, meteorological data, etc. The proposed research also addresses some of the issues related to the first proposed aspect of capacity building, responsible stewardship — by offering an example of how to associate a recommendation and synergy-finding functionality to a large data set.

There are several teams working on improving access to scientific literature [87, 136, 135, 83, 41]. There is a vast literature on recommendation systems [109]. Other recommendation systems for scientific information have been proposed in the past [64], and personalization is invoked in current web services, such as [108]. We propose a novel integration of four aspects of making access to Big Data represented in scientific preprint archives more effective. These are:

**Representation.** We will create new models based on probabilistic topic models, extending Latent Dirichlet Allocation (LDA). Casting the problem of predicting a user’s valuation function in a probabilistic framework will allow us to reap the benefits of both latent semantic representations [32, 19] and matrix factorization (dimensionality reduction) of user preferences. We will use Bayesian non-parametric methods to let the data determine the cardinality of the representation, and develop user-based methods of inference so that users of the system can suggest useful ways to change their own profiles. These representations will also be combined, in non-linear fashion, with indexing information already used in the arXiv.

**Complex Valuation.** Going beyond current valuation methods (e.g., the Netflix competition, see [109] for a recent review), we model the joint utility of sets of items and their interdependencies. This can (a) account for redundancy and synergy of items, (b) model non-modular and non-linear utility functions that hedge against model uncertainty, and (c) recommend sets or portfolios of articles that cover multiple topic areas.

**Exploration.** We will develop algorithms that efficiently probe user preferences. By deviating, in precisely calculated ways, from presenting the set of articles with the greatest estimated value to the user, the techniques to be developed will collect training data that better explores users’ preferences. This will improve overall recommendation quality [93, 116, 40], and moderate the Matthew effects, which will tend to increase the recommendation rate for whichever data items happen to be recommended first.

**Continual Evaluation.** These innovations in representing, in modeling the value of sets, and in exploring the user’s preferences will all be rigorously formulated, integrated, and evaluated in a series of designed experiments using our new interface to arXiv, based at Rutgers. Efficient experimental design will extract needed information about the effects of specific innovations and their combinations, while minimizing the burden on the users of the system.
All experiments will use our enhanced front end to arXiv, (Figure 2). Current features which will be used as a baseline, and which will contribute to our models include the submission date, the finest applicable category label (e.g., “Machine Learning”), metadata (title, author, abstract). We have developed our own full-text search engine, replacing the older (TJ) experimental full-text search engine. The new front end will reward individual researchers, and will improve the effectiveness of the overall scientific process, which can be currently distorted by authors who game the system using presentation artifacts [51].

3 Plan of Research and Results of Prior Research

This research aims to develop new models for integrating the algorithmic analysis of Big Data with observation of the (active collaborative) behavior of the users of that data. It is proposed that this will accelerate discovery of new science and of changing patterns of behavior and of researcher interest. The components will address these specific challenges of interacting with (scientific) information: (1) the discovery of synergetic data sets, whose value is superlinear; (2) the representation of data elements by non-linear combination of conventional features (based on generalized terms) and derived “topical” features (based on interrelations amongst the data items and the activities of users); (3) optimal exploration and probing of the users range of interests, using dynamic programming and Gittins indices to form “probe sets,” which improve the system’s profile representing the user’s interests. A recommender system will provide ongoing rewards to users, for sharing their valuations of the data sets. Efficient experimental design will continuously assess various algorithms implementing each of these components of the research, and the (factorial) effects of presenting them in combination. Follow-up interviews with willing users will provide rich contextual information about the impact of the system on their research activities.

Each research component seeks a potential breakthrough in the organization of, and access to, big data. By studying them jointly the proposed research: (1) reduces the delays of conventional research, which waits upon review and publication for developments in one component to influence research in another; and (2) makes it possible to observe synergies among the innovations (“interaction effects,” in the language of experimental design) that are invisible if each component of the research is carried out in isolation. All research results and code will be shared under open-source models, as we have done in previous research. Prior results on the several components of the research are discussed component by component below.

Advantages of the Research Setting. The arXiv is an excellent research site, with hundreds of thousands of visits every day. We can draw on multiple representations, ranging from keyword search, to browsing the metadata, to downloading the full text of a paper. Nearly all accesses since the creation of the arXiv in 1991 have been preserved, and are available for offline evaluation and user simulation. These will let us study topic and interest shifts providing information on the semantic structure of the collection [100]. The volume of data to which we have access is small compared with the flow at major global search sites. However, having full control over the arXiv resource provides valuable flexibility during method development and a starting point for scaling up. Our front end to arXiv lets users personalize at the thematic level, or persist personalization over all their searches. We will also let them specify among the inferred topic areas. The system will leverage their actions for implicit feedback, and use their valuations (see Figure 2) for explicit feedback on multiple levels of granularity.

3.1 Research Thrust 1: Representation

Our system for guiding search and recommendation of scientific articles must manipulate and learn good representations of users and articles. We base these representations on probabilistic topic models. Topic models provide a lever for computing about the underlying meanings of articles, elucidating similarities among articles with similar themes. Further, topic models give us a way to further exploit metadata structure [90], such as time [16] or citation [27]. Finally, topic models help situate users into a semantic space that they can interpret and understand.
3.1.1 Background: Probabilistic Topic Models

Topic modeling algorithms infer the hidden themes that pervade a corpus of articles [19, 122]. These themes are represented as weighted collections of words, which are called “topics.” The topics span a low-dimensional meaning space, which we fit to observed documents. We (DB) have developed Latent Dirichlet Allocation [19], a topic model that has become a building block for many other models [7, 10, 14, 16, 17, 12, 22, 24, 28, 38, 44, 49, 57, 82, 81, 85, 89, 96, 95, 102, 110, 111, 128, 138, 144, 153]. For a review of this field, see [18, 11].

LDA posits a set of latent topics describing the collection, and that each document exhibits a subset of the topics, with specific intensities. As in [97], it extends mixture models used in the context of text classification, where each document is limited to exhibit one topic. It extends earlier topic- or concept-based models such as Latent Semantic Indexing (LSI) [32] or the Probabilistic Latent Semantic Indexing model (pLSI) to a modular generative probabilistic model. One can also view LDA as a probabilistic variant of non-negative matrix factorization [122, 23, 71]. The tautological limitation that flows from working in a reduced space of factorizations is compensated for by (1) the increase in meaningfulness to the user and (2) the potential of non-linear combination of topic models with conventional representations.

LDA is extendible, and can be easily embedded in more complicated models—particularly relevant to our application are those that include user activity [141] and those that take into account topics changing over time [16, 145]. Topic models have been extended to Bayesian nonparametric settings, i.e., to flexible models that can learn the number of topics from the data and allow new data to initiate previously unseen topics [128]. This is particularly pertinent to building a long-term running system for dealing with Big Data.

In Bayesian terms, analyzing data with LDA amounts to performing posterior inference, i.e., computing the distribution of the hidden topic structure conditioned on the observed collection of documents. In LDA, this hidden structure comprises the distributions over terms associated with each topic, the topic proportions associated with each document, and the topic assignment associated with each word. We use the posterior distribution to relate words to the unobserved topics and “fill in” the hidden topical quantities. These filled-in quantities can then be used for recommendation, estimation of set values, and for exploration. LDA topics have been successfully applied to information retrieval [146], classification [19, 39], and browsing a document collection in a topic-guided way [17, 50, 89, 95, 96]. LDA and matrix factorization have also been successfully used in some recommendation algorithms [141, 3, 71].

Exact inference for LDA is not computationally feasible. We (DB) have developed several mean-field variational inference algorithms for topic modeling [19, 54, 88]. Other approaches to approximate inference in LDA include collapsed Gibbs sampling [122], expectation propagation [91], and collapsed variational inference [129]. In this project we will use and build upon online topic modeling [54, 143, 88], which give scalable algorithms for massive collections.
3.1.2 Research Challenges

As mentioned, the recommendation of new items to the user, is key to eliciting user feedback, and to adding value to the system. The system will be able to recommend older articles that others have read, but also new articles that have not yet been read by anyone. We recognize that all the components of the problem change and drift—users’ interests change over time, new articles appear every day, our collective knowledge grows in new ways. Finally, this all must operate at scale: there are hundreds of thousands of articles and tens of thousands of users. Our representation must support these assumptions and activities.

We will represent both articles and users in topic space. Topic representations provide vital data for forming predictions of what a user will like (Section 3.2) and for guiding the system sequentially, showing articles in a way that both satisfies the user and helps the system learn more about her (Section 3.3). But doing this requires several significant advances in the state of the art.

In particular, our representation is based on a new Bayesian nonparametric dynamic topic model for text and user data. Our model is fit sequentially with online inference. Our model (a) accommodates a changing number of topics; (b) allows topics to drift and change; (c) uncovers a hidden set of connections between documents; (d) is guided by user feedback; and (e) represents users as well as documents by low-dimensional topic vectors. Broadly, the research will represent significant advances in topic modeling, Bayesian nonparametric statistics, and unsupervised learning.

**Topic Models with User Information (Years 1-4).** Topic modeling, as described here, is unsupervised learning—the documents arrive unlabeled and algorithms both discover topics and assign them to documents. Our feedback mechanisms will require additional formalisms, which accept user feedback at each iteration of the inference algorithm. We will tie the user into the topic model, by using the same latent topic space to represent user preferences over documents or sets. The interaction between representations of the users, and those of the documents, supports estimation of the value, to each user of each document. User actions provide information both about the user and the document—what the user is interested in and what kind of user is interested in the document. These are represented in topic space. Finally, both document representations (i.e., who is interested in it) and user representations (i.e., what each user is interested in) drift and change through time.

In pilot work, we developed a recommendation model based on user libraries of scientific articles [141], which won the Best Student Paper Award in KDD 2011. This model represents items and users by a vector of topic weights, and relates the probability that a user will value a document to the similarity of the two vectors. Each article is also annotated with a topic correction, which captures the fact that some articles (e.g., one about “computer vision”) might be interesting to users in other fields (e.g., “machine learning”). The topic correction vector allows the model to see—from the activity of other users—which kinds of users tend to like an article. The model’s predictions then correct for the disparity between those users’ interests and the contents of the text. For example, in a corpus from CiteULike, we identified that the original paper which introduced the expectation-maximization algorithm [33]—an algorithm that has had a tremendous impact across many applied areas—was interesting to readers of many fields. Classical collaborative filtering, which does not take content into account, cannot give such interpretable representations of users or articles. This kind of model gives better empirical predictions than classical methods, and gives an interpretable space that can be visualized and browsed as additions to the recommendation system.

We applied this model to pilot data from the arXiv. In Figure 4, we illustrate some examples of this analysis. We also measured cross-validated recall for both articles that have been seen by other users (“in-matrix”) and articles that have never been seen (“out-of-matrix”). **At 200 retrieved articles, recall for in-matrix articles was 73%; recall for out-of-matrix articles was 58%**. Note that traditional recommendation systems cannot make out-of-matrix predictions.
Hierarchical Distance-Dependent Chinese Restaurant Processes (CRP) (Years 2-5). The themes in real-world sequential corpora drift and change over time—as do user preferences—and unsupervised topic modeling must accommodate this reality. Previous attempts, [16, 142, 145, 6], cannot account for uncertainty surrounding the number of topics or they do not permit documents to exhibit multiple topics, which is essential when modeling scientific text (and is a feature of models such as LSI and LDA). Further, in other real-world sequential Big Data streams—such as intelligence reports, news, or blog data—the appearance of a topic in one document may indicate that this topic will be salient in documents nearby in time, space, or other indicators of provenance, such as geography. This phenomenon can not be captured by existing methods.

We will develop a topic model to address these limitations, and to incorporate user valuations, as described above. Specifically, we will extend the distance dependent CRP [13] (dd-CRP, developed by co-PIs DB and PF) to a hierarchical model accommodating documents having multiple topics, whose number is determined by the data and which may drift over time. The document time-stamp plays two roles. First, it indexes the amount of drift in the topics, as in the continuous-time dynamic topic model [142]. Second, it coordinates the relative proportions of the topics; topics that appear in nearby documents should be more likely to appear than topics that are seen only at remote times. (Similar considerations apply to the user representations.)

Further, we will develop fast approximate inference methods for analyzing large data sets with the hierarchical dd-CRP. We will develop variational inference algorithms [137] as an alternative to Markov chain Monte Carlo (MCMC) sampling methods. Variational inference techniques exist for the CRP mixture models [15, 74] and hierarchical Dirichlet Process (DP) mixtures [130], but dd-CRPs currently rely on MCMC. We will develop a novel variational algorithm for standard DP mixtures (i.e., those with no external data point dependence). Recasting standard DP mixtures as distance dependent CRPs has already yielded new and better MCMC algorithms, and we expect these advantages to persist in the resulting variational inference algorithms [12]. Finally we will develop online variational inference, like that developed by co-PI Blei for other hierarchical Bayesian nonparametric models [143], to adapt these methods to streaming data.

Incorporating Side Information (Years 3-5). The flexible topic model represents both articles and users in topic space in order to form predictions about which article a user will like. An advantage of representing users in an interpretable space is that we can allow them to interact with their representations, guiding our representation of their interests to suit specific needs (or correct for the user’s self-impression). The algorithm will provide an initial representation and allow the user to examine and adjust it. Further, the user might want to adjust the topic representation of articles that she authors. (There is little prior work on this idea, though see the recent “Interacting Topic Models” of [55].)

We will formulate a so-called “spike and slab” (S&S) prior distribution [56] for document proportions and user representations, with an indefinite number of components. The S&S distributions on the simplex have been developed for topics [139], but only for a fixed number of components. S&S models with indefinite numbers of components will require more complicated structures, such as the Indian Buffet Process (IBP) [48, 130]. (The IBP extends CRP methods to latent feature models, as opposed to latent partition models.)

The IBP model will allow users to turn on and off “occurrence” bits for topics, a relatively intuitive way to interact with the model. For example, a user might “turn off” her interest in Computational Biology when searching for articles that focus on theoretical machine learning. In addition to the modeling challenge, this leads to inference challenges. With a human in the loop (and especially one waiting for results) any inference must be very fast. We will develop scalable online inference to adjust the current predictions to incorporate such kinds of side information.
3.2 Research Thrust 2: Complex Valuation

Topic models enable a richer, yet more compact encoding of user models. We use their low-dimensional representation to develop more realistic and sophisticated models of user preference. In particular, we will develop user models that remove the (unrealistic) assumption that the utility of an item (in this setting, a research article) does not depend on other items presented to the user. This common technical assumption fails in at least three ways, for many, if not most, real-world settings. **First**, it ignores redundancy and synergy among items. A user may care about small revisions to an article in his core area of interest; in secondary areas of interest the user wants to avoid such redundancy. **Second**, often users seek an overview of several topics rather than wanting to focus only on one dominant topic of interest. For example, a user interested in dark matter might not value alerts and updates covering only dark matter; a mixed portfolio of topics would have higher value to the user. **Third**, the perceived value of a set of items often changes non-linearly with the number of relevant items delivered. For example, a reader who only wants to know what some previously unseen topic is about, and who is presented with ten items realizes most of the value as soon as she encounters one comprehensible explanation. This suggests the value of “hedging” the presented set with respect to uncertainty about the user’s immediate preferences.

To address these three problems, we directly model the value (or utility) $U(u, D)$ of a set $D = \{d_1, ..., d_k\}$ of items to user $u$. We drop the assumption that the overall utility $U(u, D)$ is a sum of the individual utilities $U(u, d_i)$, and so $U(u, D) \neq \sum_{d \in D} U(u, d)$. While general non-linear utility functions offer great flexibility for modeling dependencies among the documents $d_i$, we must restrict the class of functions to make both learning and inference tractable. Leveraging research on Structural Support Vector Machines (SVMs) [127, 133, 61] and Conditional Random Fields [75], we focus on functions of the form $U(u, D) = w^T \Psi(u, D)$ where $w$ is a vector of parameters to be learned. Such models are known to lead to efficient and effective learning algorithms, being linear in the parameters $w$, but non-linear in $D$ and $d$. Each $\Psi_i(u, D)$ is a (kernelized) joint feature function [134] that returns a feature vector relating the properties of a user $u$ to those of set $D$. Often, $\Psi(u, D)$ can be based on a probabilistic graphical model of interactions between $u$ and $D$, or on similarities among the documents within $D$. Furthermore, $\Psi(u, D)$ can include features derived from conventional recommendation methods [72, 109]. We envision models of this type that integrate information from multiple users or user groups, particularly those identified via “topic modeling” over users instead of documents, to enable collaborative learning [86].

For many such models we know how to find the set $D$ that (approximately) maximizes utility $U(u, D)$, making it tractable to compute the set $D^* = \arg\max_{D \in A} U(u, D)$ of maximum utility, despite an exponentially-sized space $A$ of possible document sets. Note that linearity in the parameters $w$ ensures that these models inherit many of the desirable properties of linear models. In particular, we (TJ) have shown that models of this form can be trained efficiently using Structural Support Vector Machines [133, 59, 62, 60]. Our training algorithms run in polynomial time with respect to $|D|$, and in linear time with respect to the number of training examples. Techniques resulting from this line of research, which received the ICML05 Best Paper Award (BPA) [58], the KDD06 BPA [59], and the ECML09 BPA [62], are the basis for the research challenges detailed below.

### 3.2.1 Research Challenges

Each of the three research challenges addresses a limitation of conventional models in which utilities of documents are assumed independent and additive.

**Proposing Sets that Optimize a Portfolio (Years 1-2).** We will explore efficient models and learning algorithms for identifying a set of items that best serves the user’s information need. More formally, given a collection of items $C$ (e.g., new arXiv submissions since the user’s last visit), we seek a subset $D = \{d_1, ..., d_k\}$...
\{d_1, ..., d_k\} \subseteq \mathcal{C} that maximizes the value (utility) \(U(u, D)\) to the user. Note that the function \(U(u, D)\) not only models the utility of individual documents, \(d_i\), but also permits dependencies among all items in \(D\) (e.g., don’t show more than two review articles). To make computing \(D^* = \arg\max_{D \in \mathcal{A}} U(u, D)\) feasible, we start by considering monotone submodular set functions as a model of \(U(u, D)\) \([149, 37, 106, 36]\). Submodular functions are an attractive choice due to their “diminishing returns” property which naturally models redundancy. Thus, they can assign lower utility to sets \(D\) with several documents on the same topic, than to sets covering more topics. Other models beyond monotone submodular set functions, like Determinantal Point Processes \([73]\), have similar properties, and we will explore them in our research.

The value function \(U(u, D)\) is unknown and must be learned. For training data, the learning algorithm will elicit set-based feedback. For example, we can elicit feedback on which articles to delete or add to the proposed set \(D\) so the utility of the new set \(D'\) is larger (i.e., \(U(u, D') > U(u, D)\)). Little is known about learning to build such portfolios, and existing approaches \([34]\) require a complex combination of learning methods.

Any algorithm for learning such set-based utility functions must balance two factors. First, it must learn which documents a user is interested in. Second, it must learn the dependency structure among documents as it affects value. Our initial results suggest that this problem can be approached in an online learning setting. In particular, we have recently proposed \([120, 107]\) an online learning algorithm with strong theoretical guarantees, which can learn utility functions of the form \(U(u, D) = w^T \Psi(u, D)\) where \(\Psi(u, D)\) is a submodular feature map \([149, 106]\). At each time step, the algorithm presents a ranking \(D\) and receives an improved ranking \(D'\) as feedback from the user (i.e., \(U(u, D') > U(u, D)\)). Such preference feedback might even be extracted from implicit feedback. If the recommendation system presents the ranking \(a, b, c, d, e\) and receives clicks only on \(c\) and \(e\), we might infer that \(U((u, (c, e)) > U((u, (a, b))\). For such set-valued preference feedback, we have proven theoretical bounds on the prediction performance of our algorithm which hold under minimal assumptions \([120, 107]\).

Our pilot experiments with simulated users on the RCV1 Corpus \([77]\) are promising (see Figure 5). The task is to select a set of five documents that cover all five topics interesting to the user. The algorithm proposes a set \(\tilde{D}\), and receives an improved set \(D'\) as feedback. We compared the submodular model \(\sum w_i \max_{d \in D} (d_i)\), where \(d_i\) is the weight of word \(i\) in document \(d\), with the conventional independent model \(\sum w_i \sum_{d \in D} (d_i)\). Figure 5 shows that the submodular model covers, on average, more than three of the five topics after about 30 learning iterations, while the conventional approach still does not match this performance after 500 iterations.

We anticipate that learning will be even faster when topic-based features are added to the current word-based representation.

Note that other data-distillation tasks also follow the form of this portfolio-prediction problem (e.g., extractive document summarization \([84]\)). This will extend the impact of our machine learning methods to other problems.

**Proposing Sets that Hedge against Uncertainty (Years 2-4).** Set-based utility functions can model and reduce the effects of uncertainty about the user’s information need. As an extreme example, consider the problem of recommending papers, if one cannot know whether today the user is seeking a paper on an experiment or on theory. Formally, this uncertainty can be expressed in the Random Utility Model \([20, 132]\); the user does not have a single static utility function, but has a utility function \(U_t(u, d)\) that is a random draw, i.i.d., from a user-specific distribution at each \(t\). As in the example of an unfamiliar topic, above, a proposed set \(D\) may have almost maximal utility if even a single item in the set \(D\) has large utility \(U_t(u, d)\). In the extreme \(U_t(u, D) = \max_{d \in D} U_t(u, d)\). Thus, set-valued utility functions allow the learning algorithm
to mitigate uncertainty about the user’s need across the distribution of $U_t(u, d)$. Note that this is different from minimizing redundancy as discussed in the previous section, where the set-based feedback revealed a deterministic or static utility function.

We will develop learning methods to optimize set-based utility functions $U(u, D)$ in the Random Utility Model. While the system proposes a set $D$, knowing the structure of the utility function will allow us to use item-level feedback as training data. This directly ties into the exploration models of Section 3.3, since the expected (submodular) utility maximizer in the Random Utility Model is naturally diverse. Beyond the arXiv recommendation system, our algorithms will apply to diversified retrieval more generally [25, 29, 151, 104, 149, 126, 31, 150]. There, uncertainty about the user’s utility function is considered to reflect query ambiguity. Although diversified retrieval has recently attracted much interest, the problem of automated learning (as opposed to hand-coding) diversified retrieval functions is still largely unsolved.

**Beyond Sets (Years 4-5).** We will consider models for proposing items in the form of other structures beyond sets. For example, some set-based models will directly extend to rankings, by treating a ranking as a collection of nested sets. But rankings are not the only structures for presenting results [21]. A system may want to propose a tree-shaped structure of documents, which users can browse. Based on an initial ranking (i.e., the leftmost branch of the tree), the user can interactively expand promising results, thereby revealing subtrees which, at the same time, elaborate on his information need.

We (TJ) have recently shown, through both theoretical arguments and simulations, that such dynamic retrieval models can substantially improve retrieval performance for ambiguous queries [21, 106]. By enabling goal-directed browsing in the results, such tree-based models can both mitigate uncertainty about the user’s utility functions and provide a set-based portfolio. However, there are not yet any learning algorithms that can learn such tree-based models from user feedback.

### 3.3 Research Thrust 3: Exploration of User Interests

The system must handle new documents, new users, and changing preferences. To do so, the system must learn from user feedback, explicit and implicit. To accelerate learning, we might like to recommend *those articles on which feedback would most improve our model of the user’s need*. But users will soon abandon a system that presents too many irrelevant items. How should the system balance *exploration* (that is, learning preferences) with *exploitation* (using learned preferences to make recommendations)? Most Information Retrieval (IR) systems appear to concentrate on exploitation only, proposing items with the largest immediate benefit to the user.\(^3\) This is sub-optimal in the long term, creating a “rich get richer” [93, 115, 116, 40], or Matthew Effect, as popular articles are repeatedly recommended and other equally valuable articles remain undiscovered.

Recent IR research has begun to consider exploration [152, 103, 105, 148], notably at Yahoo! [4, 5, 80]. This research shows encouraging benefits, but considers settings critically different from arXiv. At arXiv the number of recent items ($I$) to recommend within a subject area (10,000) is of the same order as the number of active users ($U$) within a subcommunity ($I \approx U$). In most previous IR research, there are significantly fewer items than users ($I \ll U$). For example, [4] consider the Yahoo! front page, where $I \approx 20$ and $U \approx 20,000$ over the typical lifetime of an item. These roughly 1,000 views per item provide a surfeit of feedback.

Assumptions made in previous work focused on $I \ll U$ are not appropriate when $I \approx U$. Agarwal et al. [4] assume that users are homogeneous, or can be clustered into a number of internally homogeneous and unrelated groups. This assumption increases noise in the feedback, reducing its effectiveness. Instead,

\(^3\)There are some commercial developments recently which appear to seek a diversity of results, as when there are several persons with the name "Paul Kantor." Currently at Google a search yields 7 hits for the violinist, and one each for the political scientist, the taxidermist, and the co-PI of this proposal. Bing yields 2,1,1,2 respectively, and a hospital staff member. Yahoo is even more diverse.
we will use statistical models that better leverage similarities among users and documents [140, 3, 2, 114]. These exploration methods are related to methods for “multi-armed bandits with dependent arms” [99] and “contextual bandits” [76, 80], and our results will bear on these problems.

The $I \ll U$ assumption also appears in work finding worst-case non-Bayesian guarantees on regret [80], where it is necessary for good performance. Much previous exploration research [8, 9, 26] has focused on such worst-case analysis. To achieve practically relevant results in the difficult $I \approx U$ case, we will instead focus on finite-time average-case performance in a Bayesian framework. This Bayesian approach, enabled by representation using the models of Section 3.1, yields methods that perform well most of the time, if not in unlikely worst-case scenarios. This difference in approach will yield qualitatively different algorithms, and solutions for the case $I \approx U$ will enable recommendation despite ever-increasing collection sizes.

For the case $I \approx U$, we will: (1) develop exploration methods that better leverage similarities between users and documents to learn from limited amounts of data; (2) use a Bayesian framework to develop methods with good finite-time average-case performance; (3) combine topic information with other document and user covariates to estimate which users will be interested in a document before any recommendations are made; and (4) incorporate richer forms of feedback beyond item relevant/non-relevant judgments. Initial steps in (1-3) have begun under our EAGER grant.

Figure 6 shows results from our pilot study of a Bayesian exploration strategy contrasted to the exploit-only strategy, on historical data from the arXiv. This exploration strategy uses the topic model of [140] together with a Bayesian multi-armed bandit analysis. It recommends, to user $i$ that document $j^*$ given by $j^* = \text{argmax}_j E[\hat{u}_i^T v_j] + \nu(\text{Var}[\hat{u}_i^T v_j], \gamma_i, \sigma)$. Here $v_j$ is a latent vector of topic-based features characterizing document $j$, $\hat{u}_i$ is a vector of estimated user preferences for these features, $\gamma_i$ is a discount factor modified to account for the arrival rate of users with preferences similar to $\hat{u}_i$, $\sigma^2$ is a measurement variance characterizing the variability of user response, and $\nu(\cdot, \cdot, \cdot)$ is the appropriate Gittins index [45]. The vector $v_j$ includes not just the topic proportions, but also a latent adjustment learned from user feedback [140]; $v_j$ could also include document features not based on topics. Pure exploitation uses the same statistical model, but simple recommends the document with the largest posterior mean, $j_{\text{exploit}}^* = \text{argmax}_j E[\hat{u}_i^T v_j]$.

Figure 6 plots the average number of relevant documents presented to each user, as a function of the average total number of documents presented. We use historical data from the arXiv and simulated users, with $I \approx 2.5 \times U$. (We are currently conducting a live study under our EAGER grant.) Exploration yields a 30% increase in relevant documents. Such excellent performance when $U \approx I$ results from our focus on the average case, Bayesian priors based on document features, and the ability of the underlying statistical approach to model user similarity.

Our experiments will compare against existing bandit [4, 5] and active learning [79, 78, 117, 119, 43] methods. Active learning usually assumes a fixed cost for feedback from the users (for exceptions see [70, 67, 118]), recommending many irrelevant articles. Thus, our baseline will “occasionally” explore with active learning, and otherwise exploit.

### 3.3.1 Research Challenges

**Efficient Exploration with Established Users (Years 1-2).** Recommending new articles to established users simplifies exploration, since established users have substantial query and browsing histories, and may have provided a user profile or many ratings. They can be reasonably treated as having known preferences across features and topics as in [140]. The exploration can focus on rapidly learning which new items best
express these topics. We will pursue approximate look-ahead strategies such as [112, 113], and methods using restless bandits [147, 98, 47] and bandit linear optimization [1]. We have begun this research under our NSF EAGER grant.

**Rich User Feedback (Years 2-4).** We will seek to make exploration more efficient by incorporating richer feedback from users. Users do not only evaluate the items provided to them; they also browse, query, and, in our system, will eventually be able to create profiles. If, given a set, the user requests “more articles similar to” one item and ultimately values an article not among those recommended, this gives us feedback about all of the articles displayed, as described in Section 3.2. This alters the way in which exploration should be performed. A key deep question is whether this type of feedback admits online learning algorithms requiring only logarithmic amounts of data (as in the expert setting) or requiring linear amounts of data (as in the bandit setting).

**Exploration and Diverse Recommendations (Years 4-5).** Diversifying the collection of items presented should accelerate learning the preferences of new users. We will use a variant of the random utility model (see Section 3.2), where the prior model for the user preferences is a mixture over distinct user preference profiles. When the user is modeled as choosing the best from among the recommendations provided, the resulting Bayes-optimal exploitation strategy automatically produces diverse recommendations. The user’s choice among the diverse recommendations offered will then allow the algorithm to better learn his preferences. We will also develop Bayesian exploration for more general forms of user utility \( \mathcal{U}(u, D) \) for sets of documents \( D \), by modeling \( \mathcal{U}(u, D) = w^T \Psi(u, D) \) (as in Section 3.2), placing a prior on the unknown weight vector \( w \), and considering the resulting Bayesian exploration problem.

### 3.4 Research Thrust 4: Continuous Evaluation, Controlled Experiments

To evaluate the technologies being developed we will apply them to specific domains: the scientific preprints maintained at the arXiv. We will assess the technology and we will track and assess engagement, and other such activities, by users of the arXiv. Users may opt among several different levels of engagement and personalization, as described in the supplementary document dealing with human subjects. The evaluation plan will assess behavior of, and benefits to thousands of individual users of the arXiv, and is appropriate for the size and scope of this project.

The experimental design includes online and offline experiments, with both subjective and objective data integrated using multivariate analysis of covariance. Our pilot study established that usage levels at arXiv (\( \approx 10^5 \) events per day) are adequate to provide rapid growth of the system data sets. For typical users (>3-4 uses per week) the benefits found in simulation experiments should appear in two or three weeks. This is a conservative bound, as a more effective system will motivate users to provide feedback more often.

#### 3.4.1 Baseline and Experimental System

Our front end to the arXiv is able to monitor users’ interactions, obtaining both implicit feedback (click-stream information), and explicit feedback (user valuations) at multiple levels of granularity. It is seamlessly integrated with the arXiv engine, with the server for http://my.arxiv.org located on the Rutgers campus. We track user accesses through the arXiv metadata pages by url-rewriting and JavaScript. We store value judgments (implicit and explicit) and can explore algorithmic innovations in offline experiments.

#### 3.4.2 Measures of Effectiveness

There are many standard measures for ranking and recommendation including pointwise measures such as: precision at 5 \( (p_5) \); Normalized Cumulated Discounted Gain; Mean Reciprocal Rank; and variants of precision, recall, and the F-measures. Results from our preliminary experiments on complex set-based valuation, and on exploration are shown in preceding sections. In the proposed work, the key measure of value to
the user will be the set-based function $U(u, D)$ for user $p$. We will elicit this implicitly (by tracking click-through) and explicitly, by identifying where the items (or combinations of items) that the user values highly appear in the ranked lists. Thus, if the user identifies items at ranks $r_{i_1}, \ldots, r_{i_K}$ as constituting the most valuable subset of the presented items, alternative algorithms can be assessed by how highly they place the first element of valued set to appear in their rankings, and how many items must be examined in order to find them all. Note that this is an asymmetric measure, since the alternative may have produced its own “best subset” which is quite different from the one produced in the first instance. Symmetrized measures will be developed and validated. The assessment of any algorithm (or portfolio of algorithms) will look at the improvement in score, over time, as the system “learns more about the specific user.”

### 3.4.3 Collecting Additional Data from Users

We will do online real-time collection of feedback from users and offline follow-up interviews, using Skype, as appropriate. The research front end to the arXiv system presents familiar features of the present system, (see Figure 2) and accepts active valuation (the small fonts below the item information). The evaluation process currently does $A/B$ comparisons between methods, by interleaving results produced by two different algorithms ($A$ and $B$). For set-based valuation the experimental design must be expanded so that entire sessions (or entire pages within a session) are assessed jointly. The underlying mechanism remains a set of $A/B$ comparisons but $A$ now represents a triple of methods (valuation; exploration; representation) [63]. We will also extend current clickthrough mechanisms to gather more information. The analysis of implicit information takes into account the effects of ordering, which are well-studied, and can be approximated by a geometric fall-off.

**Added Information.** Telephone interviews with several dozen users each year (compensated, see Human Subjects) will yield qualitative information to guide development of our vocabulary and taxonomy for describing user goals, and for assessing the quality of the service. As appropriate we will modify the language in the interface and in the online survey site. Probe questions for those interviews assess key assumptions underlying our model development, such as: “When you search, do you have more than one theme in mind at a time? Can you give me some examples?” or “What should it indicate to the system when you click on a link?” A planned extension will permit users to define the theme (e.g., by specifying multiple folders) with respect to which the valuation judgment is made. These will complement algorithmic topic discovery, and will support trend analysis of the topics as well.

To untangle the joint effects of representation, valuation system, and the exploration, on overall user valuation, with data measured in thousands, rather than millions of items, we will use factorial experimental designs [53, 52, 131]. We (PK) have applied such design to question-answering systems [68, 69, 124]. In that arena a searcher cannot repeat any specific task using more than one algorithmic variant. In the arXiv research setting, most users have ongoing research interests, which permits repeated measurement (same task and same human subject), and is more powerful than the time-limited research design used in [68, 69].

**Data Analysis.** First order (main effects) ANOVA, has proven effective in [123]. The dependent variable $y$ which may be either objective or subjective, and may be transformed (for example, logistically) before the analysis of variance. The general main effects equation is [123, 94]: $y_{uta} = \lambda^\text{User}_u + \lambda^\text{Task}_t + \lambda^\text{Algorithm}_a + \epsilon$. Here $u$ labels the specific user; $t$ labels the specific task; and $a$ labels the specific algorithm applied. The several variables $\lambda^X_x$ represent fixed main effects, while $\epsilon$ represents the unexplained noise. When the same user and task are observed in multiple sessions, random effects will be modeled as appropriate. Astonishingly small samples (in [94], as few as eight persons, doing eight tasks, and using four algorithms) can yield statistically significant results, and are able to distinguish at a 90% confidence level among the algorithms studied, at least in query-answering.

### 3.4.4 Research Challenges

**Results of Current Research.** We have developed the front end, baseline systems, and instruments and are conducting offline simulation experiments. These demonstrate that the proposed innovations can be
evaluated with the kind and volume of information produced by the front end. Interface development is being closely coordinated with algorithm development, ensuring the data needed to develop each algorithm is captured and preserved for all interactive sessions. IRB approval is discussed in the Human Subjects documents. The overall structure is that only researchers at Rutgers interact with the confidential data, while Cornell and Princeton deal only with fully anonymized data. Users of the experimental interface may choose among non-participation (that is, no data tracking) through two levels of anonymous participation (via a search pseudonym, per session, or longitudinally), to confidential participation in an interview.

**Conduct Experiments to Compare Each New Algorithm Against the Best Prior System (Years 1-5).** For each aspect of algorithmic development (Representation, Complex Valuation, and Exploration), the present arXiv methods serve as the null hypothesis. Over the project, our new algorithms and methods expand the space of design states. In each of years 2-5 cycles of complete factorial experimentation will assess at least one new alternative for each of the research directions. Online we will compare specifically against the most successful variant thus far for that direction. This kind of “tournament” approach accelerates evolution, making best use of the limiting resource, user feedback. Thus at least eight (\(= 2^3\)) combinations of algorithms will be evaluated in each testing cycle (planned at two cycles per year). Exhaustive offline experiments will be done against archived data. Revisions to interview and data collection protocols will be approved by the IRB.

## 4 Schedule of Work and Budget Justification

The work schedule is detailed in the collaboration plan. Funds are concentrated on supporting graduate students and postdoctoral researchers. The project includes one FTE programmer at Rutgers, four graduate students (Cornell and Rutgers) and one Post-Doc at Princeton, with summer support for the PIs. This structure ensures that students are focussed on research and not on programming and maintenance. Rapid prototyping and feedback among the key scientific components of the research (“extreme programming”) yields synergies, making the budget much lower than would be required to accomplish this work in separate projects.

## 5 Broader Impacts

The proposed research directly impacts education and all fields where many users are concerned with the same Big Data set. It will immediately support those sciences using arXiv.

**Curricular Impacts. Integrating Undergraduates and Developing National Capability.** This area attracts undergraduates; their work (we will seek REU funds) advances the project. Four doctoral students and one postdoctoral fellow will be supported and mentored in each of the four years. Rutgers, Princeton and Cornell all have programs to increase under-represented groups’ participation in STEM. Students will be recruited in venues that increase minority representation.

**Course Materials.** The algorithms, data, software, and findings will be used in courses at all levels at all three universities. **Undergraduate.** Co-PI PG advises an undergraduate who uses code from co-PI DB. Courses that will be impacted by the results are: “Internet and the Information Environment” (Rutgers); “Interacting with Data” (Princeton); “Machine Learning” (Cornell); “Information Retrieval” (Cornell); and “Information Systems and Analysis” (Cornell). Co-PI PF now includes a student final project on exploration for recommender systems in “Information Systems and Analysis.” At the **graduate level,** Cornell and Rutgers will each set up a class on modeling complex user goals, and on combining methods. Courses that will use the research materials include: “Language Technology” (Cornell); “Optimal Learning” (Cornell); “Information Retrieval” (Rutgers); and “Foundations of Probabilistic Modeling” (Princeton).

**Software Sharing** is described in the Data Management supplementary document.
Outreach. This project meshes with existing outreach and educational efforts at all three schools and enhances the usefulness of the arXiv, with further potential to impact research and education across those disciplines.

5.1 Impacts on Related Disciplines

In addition to their direct impact on access to scientific information at the arXiv, the algorithms, heuristics and insights to be developed will contribute to an enormous range of problems involving exploration versus exploitation, including: reinforcement learning [125]; global optimization [92]; inventory control [35]; medical decision-making [66]; emergency response [42]; and clinical trials [46].

6 Previous NSF-supported Work by the Researchers

Joint NSF Project. Results in progress from our joint project NSF “EAGER: Adaptive Methods for Scalable Dissemination and Retrieval of Scientific Information” ($299,501, 07/01/11-07/31/13) are described above. In addition: David Blei: (a) 2008 NSF CAREER “New Directions in Probabilistic Topic Models” ($549,943 07/01/08 - 06/30/13 0745520), on building models of document influence and dynamics. [20 publications]. (b) 2009 NSF FADOVA grant “Interactive Discovery and Semantic Labeling of Patterns in Spatial Data,” ($499,934, 09/01/09 - 08/31/12) on uncovering patterns in spatial image data. [no publications yet]. (c) 2010 NSF grant “Text, Neuroimaging, and Memory: Unified Models of Corpora and Cognition,” ($732,296, 07/01/10 - 06/30/13) [2 publications]. Peter Frazier: [1 paper; current EAGER project]. Paul Ginsparg: Tools for Open Access Cyberinfrastructure. (PI). ARRA OCI 0926550. $882,610. (9/1/2009-8/31/2012) Investigate and implement tools for enhancing arxiv.org infrastructure, based on information filters for assisted service discovery and selection. Thorsten Joachims: (a) NSF CAREER Award 0237381 “CAREER: Improving Information Access by Learning from User Interactions” ($400k, 9/03 - 8/08) on strategies for extracting and learning from implicit feedback. [9 publications, OSMOT retrieval software, 2005 ACM SIGKDD BSPA]. (b) NSF IIS-0412894 “Discriminative Methods for Learning with Dependent Outputs” ($270k, 8/04 - 7/07) [7 publications, SVM-align etc. software, 2005 ICML BPA\textsuperscript{4}, a 2005 ICML OSPA, 2006 ACM SIGKDD BPA]. (c) NSF IIS-0713483 “RI: Learning Structure to Structure Mappings” ($405k, 9/07 - 9/10) on methods and algorithms for predicting structured objects. [9 publications, SVM-python software, 2009 ECML BRPA]. (d) NSF IIS-0812091 “Information Genealogy” ($449,578, 09/08 - 08/11) develops methods for analyzing the flow of ideas in archival document collections. [4 publications]. (e) NSF IIS-0905467 “III: Medium: Learning from Implicit Feedback Through Online Experimentation” ($1M, 09/09 - 08/13) explores interactive experiments to improve reliability and interpretability of implicit feedback for ad hoc retrieval. [1 publication]. Paul Kantor: (a) “Novel Indexing and Retrieval of Dynamic Brain Images.” (PI) Developed and validated content-based methods for matching and retrieval of fMRI data sets, achieving performance better than 80% area under the ROC curve; 1 Post-doctoral fellow and 8 graduate students over the span of the project. NSF EIA 0205178. $2,033,722. (8/15/02-6/30/2008) [55 publications]. (b) “A Decision Logic Approach to the Port-of-Entry Inspection Problem.” (Co-PI) Dynamic programming to solve sensor sequencing problems. NSF SES 0518543 (9/1/05-8/31/08). [10 publications]. (c) “MMS: Three Special Focus Programs at DIMACS: Supplement for the Monitoring Message Streams Project.” (Co-PI) 5 graduate students; Bayesian classification of texts and topics. NSF CCR 00-87022. $560,000. (7/1/00-12/31/09) [20 publications]. (d) “DNDO: Deceptive Detection: High Risk, High Performance Strategies.” (PI) Optimal dynamic programming for sensors to detect nuclear and radiological threats; 3 graduate students. NSF#CBET-0735910 $299,886. (08/31/07-8/31/08); and DHS 2008-DN-077-ARI003-02 $159,563 (9/1/08-12/31/09). [4 publications and the SNSSTREEE software]. (e) “EAGER: Assessment of Barriers to Trusting Computer-Based Home Assistance.” (PI) An interview and survey study of how patients decide to entrust themselves to computer-based medical support devices; 1 graduate student for 2 years and 4 undergraduate REU students. NSF IIS-0945192 $299,661. (9/18/09-9/17/2011) plus 2 REU supplements. [1 paper; 2 under review].

\textsuperscript{4}Best(Outstanding|Research|Student) Paper Award
7 Collaboration Plan

7.1. Advantages of the Collaborative Format

First, working collaboratively to develop new algorithms to accelerate discovery using human knowledge ensures that ideas will be assessed and tried promptly on the arXiv site. This accelerates the customary academic cycle (publish, digest, budget and implement) which is further slowed by the fact that many academic researchers are discouraged from adopting ideas invented elsewhere. We have been working closely together, with support from the NSF EAGER program, and have already set up a working server for data collection; designed the interface; the database; and algorithms for set presentation and for exploration. Our pilot simulation results demonstrate the nature and magnitude of the impact the new algorithms can have, and show that they can be effective within the level of traffic that arXiv experiences.

Second, the component problems are each so challenging that the normal research pattern when focused on only one of them is to revert to the very simplest approach for each of the others. By addressing them together we expect to progress more rapidly on each of them. We will exploit synergies with our other funded projects, each of which is strictly complementary to the components proposed here. All software will be developed in Java, although experiments of various kinds will be done using MATLAB, CPLEX and other appropriate software. [See also Data Management and Software Sharing Plan].

7.2. Collaborative Coordination and Management

The project is set as a collaborative one. Rutgers is the lead, and responsible for evaluation, both formative and summative. Cornell will address Valuation and Exploration. Princeton will address Representation. The five principals serve as a “Board of Directors” with final authority on the selection and revision of research directions. We communicate largely by email, with Skype conferences held as required to reach final decisions on design and implementation issues (the latter including the lead programmer). Overall “COO” responsibility will be assigned to Kantor, who is experienced in managing complex multidisciplinary projects. Fiscal reporting will be handled by the business offices of the several units involved: Communication and Information at Rutgers; Computer Science at Princeton; and the Computer Sciences department and the Operations Research and Information Engineering departments at Cornell.

Some funds are allocated each year (total approximately $500,000) to support rapid implementation of algorithms at the arXiv site. We believe that this investment (less than 15% of the total project budget) will accelerate feedback between formative assessment with real users and the development of concepts and algorithms. Two programmers are involved. One, who integrates experimental interfaces in the arXiv context and is based at Cornell Libraries, is guided by Ginsparg. The lead programmer, at Rutgers, is responsible for implementing the new algorithms, development of the research database, and integration of the contents of the database with the interface. The research database with user feedback, is maintained at Rutgers at the School of Communication and Information, and is seamlessly connected to the main arXiv resources at Cornell. The programmer for this component of development (Vladimir Menkov) has substantial experience in the development of collaborative systems, both in DARPA sponsored research, and commercially at Amazon.

We have already completed all of the infrastructure steps for this project, and expect, under EAGER support, to begin collecting data this summer.
The five principal investigators have been collaborating for almost a year. Frazier has collaborated pairwise with Blei, Joachims and Kantor. Frazier and Joachims are co-located in attached buildings at Cornell, and Kantor and Blei are a few miles from each other, at Rutgers and Princeton. We use the `svn` utility, for joint development of code and documents, hosted at Cornell’s Source Forge; web conferencing (Adobe) to provide a common whiteboard during meetings; and both Skype and BTMeetMe for teleconferencing. In short the collaboration is already in place, and working very well.

In the proposed research, we will include further graduate students and the Post-Doctoral researcher ensuring that they communicate with each other, using these media, rather than working in “silos.” The pilot project supports one student, who has designed the interface shown in Figure 1, and is responsible for the IRB and human subjects aspects of the research. Each student will be closely directed by one of the PIs to ensure progress towards a worthwhile research contribution and a successful dissertation.

We are setting overall performance goals of at least 50% improvement in effectiveness although the precise specification of the measure that will be used, as we move to set-based valuation, is still under discussion.

### 7.3. Collaborative Responsibilities, Timeline and Milestones

<table>
<thead>
<tr>
<th>Year</th>
<th>Representation</th>
<th>Valuation</th>
<th>Exploration</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Chinese Restaurant Process; distance dependent CRP</td>
<td>Topic-model repr. of set-valued utility functions; online preference learning</td>
<td>Optimal solution of exactly solvable models</td>
<td>Measurement of components; refine evaluation process</td>
</tr>
<tr>
<td>2</td>
<td>Hierarchical dd-CRP; drifting topics</td>
<td>Learn and optimize non-linear utilities; determine set-based portfolios</td>
<td>Myopic exploration with topic model representations</td>
<td>Added offline experiments; online data collection; Skype interviews</td>
</tr>
<tr>
<td>3</td>
<td>Variational methods applied to dd-CRPs; topic drift</td>
<td>Learn and optimize portfolios in Random Utility Model</td>
<td>Non-myopic exploration with topic model representations</td>
<td>Interviews continue; extract synergistic effects of innovations</td>
</tr>
<tr>
<td>4</td>
<td>Add side information and user feedback; spike and slab</td>
<td>Active exploration methods for set-valued feedback</td>
<td>Myopic exploration with topic models and complex user utility</td>
<td>Overall analysis of progress; offline exploration of alternative combinations</td>
</tr>
<tr>
<td>5</td>
<td>User built into topic models directly</td>
<td>Structured valuation and feedback beyond sets; dynamic feedback</td>
<td>Non-myopic exploration with topic models and complex user utility</td>
<td>Summary experiments; best of each year in final “bakeoff”</td>
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</table>