Usher: Improving Data Quality with Dynamic Forms

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Abstract

Data quality is a critical problem in modern databases. Data entry forms present the first and arguably best opportunity for detecting and mitigating errors, but there has been little research into automatic methods for improving data quality at entry time. In this paper, we propose USHER, an end-to-end system for form design, entry, and data quality assurance. Using previous form submissions, USHER learns a probabilistic model over the questions of the form. USHER then applies this model at every step of the data entry process to improve data quality. Before entry, it induces a form layout that captures the most important data values of a form instance as quickly as possible and reduces the complexity of error-prone questions. During entry, it dynamically adapts the form to the values being entered by providing real-time interface feedback, re-asking questions with dubious responses, and simplifying questions by reformulating them. After entry, it revisits question responses that it deems likely to have been entered incorrectly by re-asking the question or a reformulation thereof. We evaluate these components of USHER using two real-world data sets. Our results demonstrate that USHER can improve data quality considerably at a reduced cost when compared to current practice.

Index Terms

Data quality, data entry, form design, adaptive form

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1 Introduction

ORGANIZATIONS and individuals routinely make important decisions based on inaccurate data stored in supposedly authoritative databases. Data errors in some domains, such as medicine, may have particularly severe consequences. These errors can arise at a variety of points in the lifecycle of data, from data entry, through storage, integration, and cleaning, all the way to analysis and decision-making [1]. While each step presents an opportunity to address data quality, entry time offers the earliest opportunity to catch and correct errors. The database community has focused on *data cleaning* once data has been collected into a database, and has paid relatively little attention to data quality at collection time [1], [2]. Current best practices for quality during data entry come from the field of survey methodology, which offers principles that include manual question orderings and input constraints, and double entry of paper forms [3]. Although this has long been the *de facto* quality assurance standard in data collection and transformation, we believe this area merits reconsideration. For both paper forms and direct electronic entry, we posit that a data-driven and more computationally sophisticated approach can significantly outperform these decades-old static methods in both accuracy and efficiency of data entry.

The problem of data quality is magnified in low-resource data collection settings. Recently, the World Health Organization likened the lack of quality health information in developing regions to a "gathering storm," saying, "[to] make people count, we first need to be able to count people" [4]. Indeed, many health organizations, particularly those operating with limited resources in developing regions, struggle with collecting high-quality data. Why is data collection so challenging? First, many organizations lack expertise in paper and electronic form design: designers approach question and answer choice selection with a defensive, catch-all mindset, adding answer choices and questions that may not be necessary; furthermore, they engage in ad hoc mapping of required data fields to data entry widgets by intuition [5], [6], often ignoring or specifying ill-fitting constraints. Second, double entry is too costly. In some cases this means it is simply not performed, resulting in poor data quality. In other cases, particularly when double entry is mandated by third parties, it results in delays and other unintended negative consequences. We observed this scenario in an HIV/AIDS program in Tanzania, where time-consuming double entry was imposed upon a busy local clinic. The effort required to do the double entry meant that the transcription was postponed for months and handled in batch. Although the data eventually percolated up to national and international agencies, in the interim the local clinic was operating as usual via paper forms, unable to benefit from an electronic view of the data latent in their organization. Finally, many organizations in developing regions are beginning to use mobile devices like smartphones for data collection; for instance, community health workers are doing direct digital data entry in remote locations. Electronic data entry devices offer different affordances than those of paper, displacing the role of traditional form design and double entry [5]. We often found that there were no data quality checks at all in naïvely implemented mobile interfaces, compounding the fact that mobile data entry quality is ten times worse than dictation to a human operator [7].

To address this spectrum of data quality challenges, we have developed USHER, an end-to-end system that can improve data quality and efficiency at the point of entry by learning *probabilistic models* from existing data, which stochastically relate the questions of a data entry form. These models form a principled foundation on which we develop information-theoretic algorithms for form design, dynamic form adaptation during entry, and answer verification:

1) Since form layout and question selection is often ad hoc, USHER optimizes question *ordering* according to a probabilistic objective function that aims to maximize the information content of form answers as early as possible — we call this the *greedy information gain* principle. Applied before entry, the model generates a static but entropy-optimal ordering, which focus on important questions first; during entry, it can be used to dynamically pick the next best question, based on answers so-far — appropriate in scenarios where question ordering can be flexible between instances.
2) Applying its probabilistic model during data entry, USHER can evaluate the conditional distribution of answers to a form question, and make it easier for likely answers to be entered — we call this the *appropriate entry friction* principle. For difficult-to-answer questions, such as those with many extraneous choices, USHER can opportunistically *reformulate* them to be easier and more congruous with the available information. In this way, USHER effectively allows for a principled, controlled tradeoff between data quality and form filling effort and time.
3) Finally, the stochastic model is consulted to predict which responses may be erroneous, so as to *re-ask* those questions in order to verify their correctness — we call this the *contextualized error likelihood* principle. We consider re-asking questions both during the data entry process (integrated re-asking) and after data entry has been finished (post-hoc re-asking). In both cases, intelligent question re-asking approximates the benefits

of double entry at a fraction of the cost.

In addition, we may extend USHER's *appropriate entry friction* approach to provide a framework for reasoning about feedback mechanisms for the data-entry user interface. During data entry, using the likelihood of unanswered fields given entered answers, and following the intuition that multivariate outliers are values warranting reexamination by the data entry worker, USHER can guide the user with much more specific and context-aware feedback. In Section 9, we offer initial thoughts on design patterns for USHER-inspired dynamic data entry interfaces.

The contributions of this paper are fourfold:

1) We describe the design of USHER's core: probabilistic models for arbitrary data entry forms.
2) We describe USHER's application of these models to provide guidance along each step of the data entry lifecycle: reordering questions for greedy information gain, reformulating answers for appropriate entry friction, and re-asking questions according to contextualized error likelihood.
3) We present experiments showing that USHER has the potential to improve data quality at reduced cost. We study two representative data sets: direct electronic entry of survey results about political opinion and transcription of paper-based patient intake forms from an HIV/AIDS clinic in Tanzania.
4) Extending our ideas on form dynamics, we propose new user interface principles for providing contextualized, intuitive feedback based on the likelihood of data as it is entered. This provides a foundation for incorporating data cleaning mechanisms directly in the entry process.

2 RELATED WORK

Our work builds upon several areas of related work. We provide an overview in this section.

2.1 Data Cleaning

In the database literature, data quality has typically been addressed under the rubric of *data cleaning* [1], [2]. Our work connects most directly to data cleaning via multivariate outlier detection; it is based in part on interface ideas first proposed by Hellerstein [8]. By the time such retrospective data cleaning is done, the physical source of the data is typically unavailable — thus, errors often become too difficult or time-consuming to be rectified. USHER addresses this issue by applying statistical data quality insights at the time of data entry. Thus, it can catch errors when they are made and when ground-truth values may still be available for verification.

2.2 User Interfaces

Past research on improving data entry is mostly focused on adapting the data entry interface for user efficiency improvements. Several such projects have used learning techniques to automatically fill or predict a top-k set of likely values [9], [10], [11], [12], [13], [14], [15]. For example, Ali and Meek [9] predicted values for combo-boxes in web forms and measured improvements in the speed of entry, Ecopod [15] generated type-ahead suggestions that were improved by geographic information, and Hermens et al. [10] automatically filled leave-of-absence forms using decision trees and measured predictive accuracy and time savings. In these approaches, learning techniques are used to predict form values based on past data, and each measures the time savings of particular data entry mechanisms and/or the proportion of values their model was able to correctly predict. USHER's focus is on improving data quality, and its probabilistic formalism is based on learning relationships within the underlying data that guide the user towards correct entries. In addition to predicting question values, we develop and exploit probabilistic models of user error, and target a broader set of interface adaptations for improving data quality, including question reordering, reformulation, and re-asking, and widget customizations that provide feedback to the user based on the likelihood of their entries. Some of the enhancements we make for data quality could also be applied to improve the speed of entry.

2.3 Clinical Trials

Data quality assurance is a prominent topic in the science of clinical trials, where the practice of double entry has been questioned and dissected, but nonetheless remains the gold standard [16], [17]. In particular, Kleinman takes a probabilistic approach toward choosing which forms to re-enter based on the individual performance of data entry staff [18]. This *cross-form* validation has the same goal as our approach of reducing the need for complete double entry, but does so at a much coarser level of granularity. It requires historical performance records for each data entry worker, and does not offer dynamic reconfirmation of individual questions. In contrast, USHER's *cross-question* validation adapts to the actual data being entered in light of previous form submissions, and allows for a principled assessment of the tradeoff between cost (of reconfirming more questions) versus quality (as predicted by the probabilistic model).

2.4 Survey Design

The survey design literature includes extensive work on form design techniques that can improve data quality [3], [19]. This literature advocates the use of manually specified *constraints* on response values. These constraints may be univariate (e.g., a maximum value for an *age* question) or multivariate (e.g., disallowing *gender* to be *male* and *pregnant* to be *yes*). Some constraints may also be "soft" and only serve as warnings regarding unlikely combinations (e.g., *age* being 60 and *pregnant* being *yes*).

The manual specification of such constraints requires a domain expert, which can be prohibitive in many scenarios. By relying on prior data, USHER learns many of these same constraints without requiring their explicit specification. When these constraints are violated during entry, USHER can then flag the relevant questions, or target them for re-asking.

However, USHER does not preclude the manual specification of constraints. This is critical, because previous research into the psychological phenomena of survey filling has yielded common constraints not inherently learnable from prior data [3]. This work provides heuristics such as "groups of topically related questions should often be placed together" and "questions about race should appear at the end of a survey." USHER complements these human-specified constraints, accommodating them while leveraging any remaining flexibility to optimize question ordering in a data-driven manner.

3 SYSTEM

USHER builds a probabilistic model for an arbitrary data entry form in two steps: first, by learning the relationships between form questions via structure learning, resulting in a *Bayesian network*; and second, by estimating the parameters of that Bayesian network, which then allows us to generate predictions and error probabilities for the form.

After the model is built, USHER uses it to automatically *order* a form's questions for *greedy information gain*. Section 5 describes both static and dynamic algorithms that employ criteria based on the magnitude of statistical information gain that is expected in answering a question, given the answers that have been provided so far. This is a key idea in our approach. By front-loading predictive potential, we increase the models' capacity in several ways. First, from an information theoretic perspective, we improve our ability to do multivariate prediction and outlier detection for subsequent questions. As we discuss in more detail in Sections 7 and 9, this predictive ability can be applied by reformulating error-prone form questions, parametrizing data entry widgets (type-ahead suggestions, default values), assessing answers (outlier flags), and performing in-flight re-asking (also known as cross-validation in survey design parlance). Second, from a psychological perspective, front-loading information gain also addresses the human issues of user fatigue and limited attention span, which can result in increasing error rates over time and unanswered questions at the end of the form.

Our approach is driven by the same intuition underlying the practice of *curbstoning*, which was related to us in discussion with survey design experts [6]. Curbstoning is a way in which an unscrupulous door-to-door surveyor shirks work: he or she asks an interviewee only a few *important* questions, and then uses those responses to complete the remainder of a form while sitting on the curb outside the home. The constructive insight here is that a well-chosen subset of questions can often enable an experienced agent to intuitively predict the remaining answers. USHER's question ordering algorithms formalize this intuition via the principle of greedy information gain, and use them (scrupulously) to improve data entry.

USHER's learning algorithm relies on training data. In practice, a data entry backlog can serve as this training set. In the absence of sufficient training data, USHER can bootstrap itself on a "uniform prior," generating a form based on the assumption that all inputs are equally likely; this is no worse than standard practice. Subsequently, a training set can gradually be constructed by iteratively capturing data from designers and potential users in "learning runs." It is a common approach to first fit to the available data, and then evolve a model as new data becomes available. This process of semi-automated form design can help institutionalize new forms before they are deployed in production.

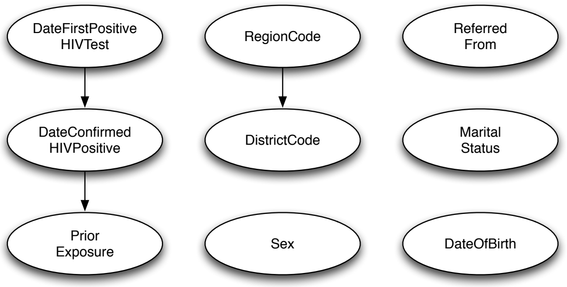


Fig. 1. Bayesian network for the *patient* dataset, showing automatically inferred probabilistic relationships between form questions.

USHER adapts to a form and dataset by crafting a custom model. Of course, as in many learning systems, the model learned may not translate across contexts. We do not claim that each learned model would or should fully generalize to different environments. Instead, each context-specific model is used to ensure data quality for a *particular* situation, where we expect relatively consistent patterns in input data characteristics. In the remainder of this section, we illustrate USHER's functionality with examples. Further details, particularly regarding the probabilistic model, follow in the ensuing sections.

3.1 Examples

We present two running examples. First, the *patient* dataset comes from paper patient-registration forms transcribed by data entry workers at an HIV/AIDS program in Tanzania.[1] Second, the *survey* dataset comes from a phone survey of political opinion in the San Francisco Bay Area, entered by survey professionals directly into an electronic form.

In each example, a form designer begins by creating a simple specification of form questions and their prompts, response data types, and constraints. The training data set is made up of prior form responses. Using the learning algorithms we present in Section 4, USHER builds a Bayesian network of probabilistic relationships from the data, as shown in Figures 1 and 2. In this graph, an edge captures a close stochastic dependency between two random variables (i.e., form questions). Two questions with no path between them in the graph are probabilistically independent. Figure 2 illustrates a denser graph, demonstrating that political survey responses tend to be highly correlated. Note that a standard joint distribution would show correlations among *all pairs* of questions; the sparsity of these examples reflects conditional independence patterns learned from the data. Encoding independence in a Bayesian network is a standard method in machine learning that clarifies the underlying structure, mitigates data overfitting, and improves the efficiency of probabilistic inference.

1. We have pruned out questions with identifying information about patients, as well as free-text comment fields.

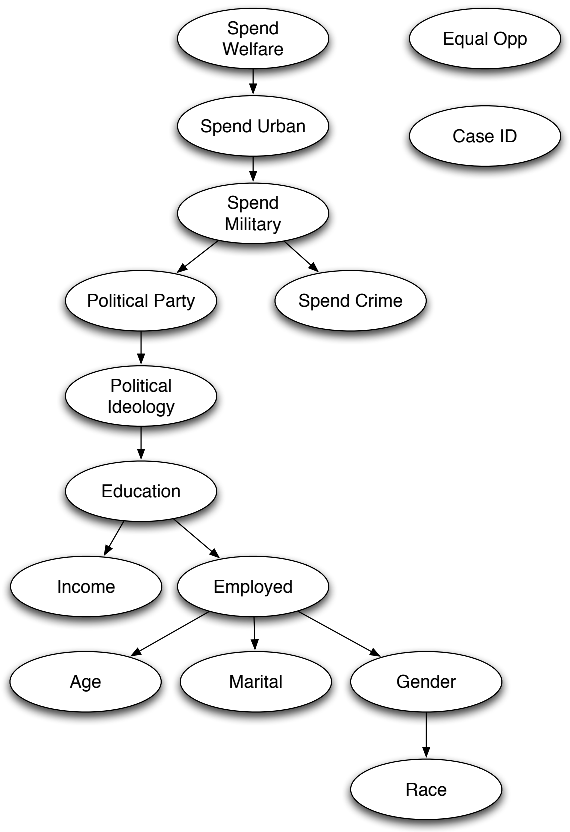


Fig. 2. Bayesian network for the *survey* dataset. The probabilistic relationships are more dense. Some relationships are intuitive (Political Ideology - Political Party), others show patterns incidental to the dataset (race - gender).

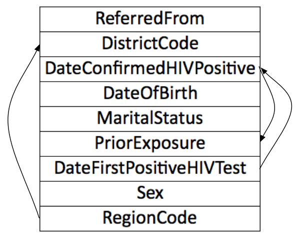


Fig. 3. Example question layout generated by our ordering algorithm. The arrows reflect the probabilistic dependencies from Figure 1.

The learned structure is subject to manual control: a designer can override any learned correlations that are believed to be spurious or that make the form more difficult to administer.

For the *patient* dataset, USHER generated the static ordering shown in Figure 3. We can see in Figure 3 that the structure learner predicted *RegionCode* to be correlated with *DistrictCode*. Our data set is collected mostly from clinics in a single region of Tanzania, so RegionCode provides little information. It is not surprising then, that USHER's suggested ordering has DistrictCode early and RegionCode last — once we observe DistrictCode, RegionCode has very little additional expected conditional information gain. When it is time to input the RegionCode, if the user selects an incorrect value, the model can be more certain that it is unlikely. If the user stops early and does not fill in RegionCode, the model can infer the likely value with higher confidence. In general, static question orderings are appropriate as an offline process for paper forms where there is latitude for (re-)ordering questions, within designer-specified constraints.

During data entry, USHER uses the probabilistic machinery to drive dynamic updates to the form structure. One type of update is the dynamic selection of the best next question to ask among questions yet to be answered. This can be appropriate in several situations, including surveys that do not expect users to finish all questions, or direct-entry interfaces (e.g., mobile phones) where one question is asked at a time. We note that it is still important to respect the form designer's *a priori* specified question-grouping and -ordering constraints when a form is dynamically updated.

USHER is also used during data entry to provide dynamic feedback, by calculating the conditional distribution for the question in focus and using it to influence the way the question is presented. We tackle this via two techniques: question reformulation and widget decoration. For the former, we could for example choose to reformulate the question about RegionCode into a binary yes/no question based on the answer to DistrictCode, since DistrictCode is such a strong predictor of RegionCode. As we discuss in Section 7, the reduced selection space for responses in turn reduces the chances of a data entry worker selecting an incorrect response. For the latter, possibilities include using a "split" drop-down menu for RegionCode that features the most likely answers "above the line," and after entry, coloring the chosen answer red if it is a conditional outlier. We discuss in Section 9 the design space and potential impact of data entry feedback that is more specific and context aware.

As a form is being filled, USHER calculates contextualized error probabilities for each question. These values are used for re-asking questions in two ways: during primary form entry and for reconfirming answers after an initial pass. For each form question, USHER predicts how likely the response provided is erroneous, by examining whether it is likely to be a multivariate outlier, i.e., that it is unlikely with respect to the responses for other fields. In other words, an error probability is conditioned on all answered values provided by the data entry worker so far. If there are responses with error probabilities exceeding a pre-set threshold, USHER re-asks those questions ordered by techniques to be discussed in Section 6.

3.2 Implementation

We have implemented USHER as a web application (Figure 4). The UI loads a simple form specification file containing form question details and the location of the training data set. Form question details include question name, prompt, data type, widget type, and constraints. The server instantiates a model for each form. The system passes information about question responses to the model as they are filled in; in exchange, the model returns predictions and error probabilities.

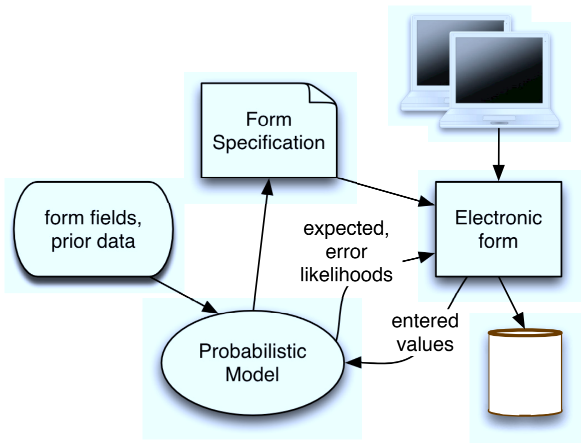


Fig. 4. USHER components and data flow: (1) model a form and its data, (2) generate question ordering according to *greedy information gain*, (3) instantiate the form in a data entry interface, (4) during and immediately after data entry, provide dynamic re-ordering, feedback and re-confirmation according to *contextualized error likelihood*.

Models are created from the form specification, the training data set, and a graph of learned structural relationships. We perform structure learning offline with BANJO [20], an open source Java package for structure learning of Bayesian networks. Our graphical model is implemented in two variants: the first model used for ordering is based on a modified version of JavaBayes [21], an open-source Java software for Bayesian inference. Because JavaBayes only supports discrete probability variables, we implemented the error prediction version of our model using Infer.NET [22], a Microsoft .NET Framework toolkit for Bayesian inference.

4 Learning a Model for Data Entry

The core of the USHER system is its probabilistic model of the data, represented as a *Bayesian network* over form questions. This network captures relationships between a form's question elements in a stochastic manner. In particular, given input values for some subset of the questions of a particular form instance, the model can infer probability distributions over values of that instance's remaining unanswered questions. In this section, we show how standard machine learning techniques can be used to induce this model from previous form entries.

We will use $\mathbf{F} = \{F_1, \ldots, F_n\}$ to denote a set of random variables representing the values of n questions comprising a data entry form. We assume that each question response takes on a finite set of discrete values; continuous values are discretized by dividing the data range into intervals and assigning each interval one value.[2] To learn the probabilistic model, we assume access to prior entries for the same form.

USHER first builds a Bayesian network over the form questions, which will allow it to compute probability distributions over arbitrary subsets $\mathbf{G} \subseteq \mathbf{F}$ of form question random variables, given already entered question responses $\mathbf{G}' = \mathbf{g}'$ for that instance, i.e., $P(\mathbf{G} \mid \mathbf{G}' = \mathbf{g}')$. Constructing this network requires two steps: first, the induction of the graph *structure* of the network, which encodes the conditional independencies between the question random variables $\mathbf{F}$; and second, the estimation of the resulting network's *parameters*.

The naïve approach to structure selection would be to assume complete dependence of each question on every other question. However, this would blow up the number of free parameters in our model, leading to both poor generalization performance of our predictions and prohibitively slow model queries. Instead, we learn the structure using the prior form submissions in the database. USHER searches through the space of possible structures using simulated annealing, and chooses the best structure according to the Bayesian Dirichlet Equivalence criterion [23]. This criterion optimizes for a tradeoff between model expressiveness (using a richer dependency structure) and model parsimony (using a smaller number of parameters), thus identifying only the prominent, recurring probabilistic dependencies. Figures 1 and 2 show automatically learned structures for two data domains.[3]

In certain domains, form designers may already have strong common-sense notions of questions that should or should not depend on each other (e.g., education level and income are related, whereas gender and race are independent). As a postprocessing step, the form designer can manually tune the resulting model to incorporate such intuitions. In fact, the entire structure could be manually constructed in domains where an expert has comprehensive prior knowledge of the questions' interdependencies. However, a casual form designer is unlikely to consider the complete space of question combinations when identifying correlations. In most settings, we believe an automatic approach to learning multivariate correlations would yield more effective inference.

Given a graphical structure of the questions, we can then estimate the *conditional probability tables* that parameterize each node in a straightforward manner, by counting the proportion of previous form submissions with those response assignments. The probability mass function for a single question F_i with m possible discrete values, conditioned on its set of parent nodes $\mathcal{P}(F_i)$ from the Bayesian network, is:

$$\begin{aligned} &P(F_i = f_i \mid \{F_j = f_j : F_j \in \mathcal{P}(F_i)\}) \\ &\quad = \frac{N(F_i = f_i, \{F_j = f_j : F_j \in \mathcal{P}(F_i)\})}{N(\{F_j = f_j : F_j \in \mathcal{P}(F_i)\})}. \end{aligned} \tag{1}$$

In this notation, $P(F_i = f_i \mid \{F_j = f_j : F_j \in \mathcal{P}(F_i)\})$ refers to the conditional probability of question F_i taking value f_i, given that each question F_j in $\mathcal{P}(F_i)$ takes on value f_j. Here, $N(\mathbf{X})$ is the number of prior form submissions that match the conditions $\mathbf{X}$ — in the denominator, we count the number of times a previous submission had the subset $\mathcal{P}(F_i)$ of its questions set according to the listed f_j values; and in the numerator, we count the number of times when those previous submissions additionally had F_i set to f_i.

2. Using richer distributions to model fields with continuous or ordinal answers (e.g., with Gaussian models) could provide additional improvement, and is left for future work.

3. It is important to note that the arrows in the network do *not* represent causality, only that there is a probabilistic relationship between the questions.

```
Input: Model $\mathcal{G}$ with questions $\mathbf{F} = \{F_1, \ldots, F_n\}$
Output: Ordering of questions $\mathbf{O} = (O_1, \ldots, O_n)$
$\mathbf{O} \leftarrow \emptyset$;
while $|\mathbf{O}| < n$ do
    $F \leftarrow \mathrm{argmax}_{F_i \notin \mathbf{O}} H(F_i \mid \mathbf{O})$;
    $\mathbf{O} \leftarrow (\mathbf{O}, F)$;
end
```

Algorithm 1: Static ordering algorithm for form layout.

Because the number of prior form instances may be limited, and thus may not account for all possible combinations of prior question responses, equation 1 may assign zero probability to some combinations of responses. Typically, this is undesirable; just because a particular combination of values has not occurred in the past does not mean that combination cannot occur at all. We overcome this obstacle by *smoothing* these parameter estimates, interpolating each with a background uniform distribution. In particular, we revise our estimates to:

$$P(F_i = f_i \mid \{F_j = f_j : F_j \in \mathcal{P}(F_i)\}) \\ = (1-\alpha)\frac{N(F_i = f_i, \{F_j = f_j : F_j \in \mathcal{P}(F_i)\})}{N(\{F_j = f_j : F_j \in \mathcal{P}(F_i)\})} + \frac{\alpha}{m}, \quad (2)$$

where m is the number of possible values question F_i can take on, and α is the fixed smoothing parameter, which was set to 0.1 in our implementation. This approach is essentially a form of Jelinek-Mercer smoothing with a uniform backoff distribution [24].

Once the Bayesian network is constructed, we can infer distributions of the form $P(\mathbf{G} \mid \mathbf{G}' = \mathbf{g}')$ for arbitrary $\mathbf{G}, \mathbf{G}' \subseteq \mathbf{F}$ — that is, the *marginal* distributions over sets of random variables, optionally conditioned on observed values for other variables. Answering such queries is known as the *inference* task. There exist a variety of inference techniques. In our experiments, the Bayesian networks are small enough that exact techniques such as the *junction tree algorithm* [25] can be used. For larger models, faster approximate inference techniques like Loop Belief Propagation or Gibbs Sampling — common and effective approaches in Machine Learning — may be preferable.

5 Question Ordering

Having described the Bayesian network, we now turn to its applications in the USHER system. We first consider ways of automatically ordering the questions of a data entry form. The key idea behind our ordering algorithm is *greedy information gain* — that is, to reduce the amount of *uncertainty* of a single form instance as quickly as possible. Note that regardless of how questions are ordered, the total amount of uncertainty about all of the responses taken together — and hence the total amount of information that can be acquired from an entire form submission — is fixed. By reducing this uncertainty as early as possible, we can be more certain about the values of later questions. The benefits of greater certainty about later questions are two-fold. First, it allows us to more accurately provide data entry feedback for those questions. Second, we can more accurately predict missing values for incomplete form submissions.

We can quantify uncertainty using *information entropy*. A question whose random variable has high entropy reflects greater underlying uncertainty about the responses that question can take on. Formally, the entropy of random variable F_i is given by:

$$H(F_i) = -\sum_{f_i} P(f_i)\log P(f_i), \quad (3)$$

where the sum is over all possible values f_i that question F_i can take on.

As question values are entered for a single form instance, the uncertainty about the remaining questions of that instance changes. For example, in the race and politics survey, knowing the respondent's political party provides strong evidence about his or her political ideology. We can quantify the amount of uncertainty remaining in a question F_i, assuming that other questions $\mathbf{G} = \{F_1, \ldots, F_n\}$ have been previously encountered, with its *conditional entropy*:

$$H(F_i \mid \mathbf{G}) \\ = -\sum_{\mathbf{g}=(f_1,\ldots,f_n)}\sum_{f_i} P(\mathbf{G} = \mathbf{g}, F_i = f_i)\log P(F_i = f_i \mid \mathbf{G} = \mathbf{g}), \quad (4)$$

where the sum is over all possible question responses in the Cartesian product of $F_1, \ldots, F_n, F_i$. Conditional entropy measures the weighted average of the entropy of question F_j's conditional distribution, given every possible assignment of the previously observed variables. This value is obtained by performing inference on the Bayesian network to compute the necessary distributions. By taking advantage of the conditional independences encoded in the network, we can typically drop many terms from the conditioning in Equation 4 for faster computation.[4]

Our full *static ordering* algorithm based on greedy information gain is presented in Algorithm 1. We select the entire question ordering in a stepwise manner, starting with the first question. At the ith step, we choose the question with the highest conditional entropy, given the questions that have already been selected. We call this ordering "static" because the algorithm is run offline, based only on the learned Bayesian network, and does not change during the actual data entry session.

In many scenarios the form designer would like to specify natural groupings of questions that should be presented to the user as one section. Our model can be easily adapted to handle this constraint by maximizing entropy between specified groups of questions. We can select these groups according to joint entropy:

$$\arg\max_{\mathbf{G}} H(\mathbf{G} \mid F_1, \ldots, F_{i-1}), \quad (5)$$

where $\mathbf{G}$ is over the form designers' specified groups of questions. We can then further apply the static ordering algorithm

4. Conditional entropy can also be expressed as the incremental difference in joint entropy due to F_i, that is, $H(F_i \mid \mathbf{G}) = H(F_i, \mathbf{G}) - H(\mathbf{G})$. Writing out the sum of entropies for an entire form using this expression yields a telescoping sum that reduces to the fixed value $H(\mathbf{F})$. Thus, this formulation confirms our previous intuition that no matter what ordering we select, the *total* amount of uncertainty is still the same.

to order questions *within* each individual section. In this way, we capture the highest possible amount of uncertainty while still conforming to ordering constraints imposed by the form designer.

Form designers may also want to specify other kinds of constraints on form layout, such as a partial ordering over the questions that must be respected. The greedy approach can accommodate such constraints by restricting the choice of fields at every step to match the partial order.

5.1 Reordering Questions during Data Entry

In electronic form settings, we can take our ordering notion a step further and *dynamically reorder* questions in a form as an instance is being entered. This approach can be appropriate for scenarios when data entry workers input one or several values at a time, such as on a mobile device. We can apply the same greedy information gain criterion as in Algorithm 1, but update the calculations with the previous responses in the same form instance. Assuming questions $\mathbf{G} = \{F_1, \ldots, F_\ell\}$ have already been filled in with values $\mathbf{g} = \{f_1, \ldots, f_\ell\}$, the next question is selected by maximizing:

$$\begin{aligned} &H(F_i \mid \mathbf{G} = \mathbf{g}) \\ &= -\sum_{f_i} P(F_i = f_i \mid \mathbf{G} = \mathbf{g}) \log P(F_i = f_i \mid \mathbf{G} = \mathbf{g}). \quad (6) \end{aligned}$$

Notice that this objective is the same as Equation 4, except that it uses the actual responses entered for previous questions, rather than taking a weighted average over all possible values. Constraints specified by the form designer, such as topical grouping, can also be respected in the dynamic framework by restricting the selection of next questions at every step.

In general, dynamic reordering can be particularly useful in scenarios where the input of one value determines the value of another. For example, in a form with questions for *gender* and *pregnant*, a response of *male* for the former dictates the value and potential information gain of the latter. However, dynamic reordering may be confusing to data entry workers who routinely enter information into the same form, and have come to expect a specific question order. Determining the tradeoff between these opposing concerns is a human factors issue that depends on both the application domain and the user interface employed.

6 Question Re-asking

The next application of Usher's probabilistic model is for the purpose of identifying *errors* made during entry. Because this determination is made during and immediately after form submission, Usher can choose to *re-ask* questions during the same entry session. By focusing the re-asking effort only on questions that were likely to be misentered, Usher is likely to catch mistakes at a small incremental cost to the data entry worker. Our approach is a data-driven alternative to the expensive practice of double entry. Rather than re-asking *every* question, we focus re-asking effort only on question responses that are unlikely with respect to the other form responses.

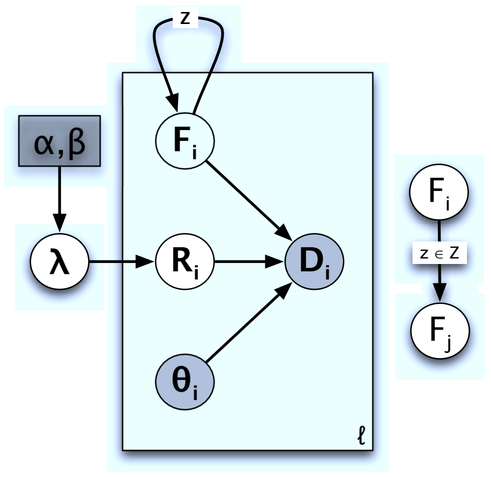


Fig. 5. The error model. Observed variable D_i represents the actual input provided by the data entry worker for the ith question, while hidden variable F_i is the true value of that question. The rectangular plate around the center variables denotes that those variables are repeated for each of the ℓ form questions with responses that have already been input. The F variables are connected by edges $z \in Z$, representing the relationships discovered in the structure learning process; this is the same structure used for the question ordering component. Variable θ_i represents the "error" distribution, which in our current model is uniform over all possible values. Variable R_i is a hidden binary indicator variable specifying whether the entered data was erroneous; its probability λ_i is drawn from a Beta prior with fixed hyperparameters α and β. Shaded nodes denote observed variables, and clear nodes denote hidden variables.

Before exploring how Usher performs re-asking, we explain how it determines whether a question response is erroneous. Usher estimates *contextualized error likelihood* for each question response, i.e., a probability of error that is conditioned on every other previously entered field response. The intuition behind error detection is straightforward: questions whose responses are "unexpected" with respect to the rest of the known input responses are more likely to be incorrect. These error likelihoods are measured both during and after the entry of a single form instance.

6.1 Error Model

To formally model the notion of error, we extend our Bayesian network from Section 4 to a more sophisticated representation that ties together intended and actual question responses. We call the Bayesian network augmented with these additional random variables the *error model*. Specifically, we posit a network where each question is augmented with additional nodes to capture a probabilistic view of entry error. For question i, we have the following set of random and observed variables:

- F_i: the *correct* value for the question, which is unknown to the system, and thus a *hidden* variable.

- D_i: the question response provided by the data entry worker, an *observed* variable.
- θ_i: the observed variable representing the parameters of the *probability distribution* of mistakes across possible answers, which is fixed per question.[5] We call the distribution with parameters θ_i the *error distribution*. For the current version of our model, θ_i is set to yield a uniform distribution.
- R_i: a binary hidden variable specifying whether an error was made in this question. When $R_i = 0$ (i.e., when no error is made), then F_i takes the same value as D_i.

Additionally, we introduce a hidden variable λ, shared across all questions, specifying how likely errors are to occur for a typical question of that form instance. Intuitively, λ plays the role of a prior error rate, and is modeled as a hidden variable so that its value can be learned directly from the data.

Note that the relationships between field values discovered during structure learning are still part of the graph, so that the error predictions are contextualized in the answers of other related questions.

Within an individual question, the relationships between the newly introduced variables are shown in Figure 5. The diagram follows standard plate diagram notation [26]. In brief, the rectangle is a *plate* containing a group of variables specific to a single question i. This rectangle is replicated for each of ℓ form questions. The F variables in each question group are connected by edges $z \in Z$, representing the relationships discovered in the structure learning process; this is the same structure used for the question ordering component. The remaining edges represent direct probabilistic relationships between the variables that are described in greater detail below. Shaded nodes denote observed variables, and clear nodes denote hidden variables.

Node $R_i \in \{0, 1\}$ is a hidden indicator variable specifying whether an error will happen at this question. Our model posits that a data entry worker implicitly flips a coin for R_i when entering a response for question i, with probability of one equal to λ. Formally, this means R_i is drawn from a Bernoulli distribution with parameter λ:

$$R_i \mid \lambda \sim \text{Bernoulli}(\lambda) \tag{7}$$

The value of R_i affects how F_i and D_i are related, which is described in detail later in this section.

We also allow the model to learn the prior probability for the λ directly from the data. This value represents the probability of making a mistake on any arbitrary question. Note that λ is shared across all form questions. Learning a value for λ rather than fixing it allows the model to produce an overall probability of error for an entire form instance as well as for individual questions. The prior distribution for λ is a *Beta* distribution, which is a continuous distribution over the real numbers from zero to one:

$$\lambda \sim \text{Beta}(\alpha, \beta) \tag{8}$$

The Beta distribution takes two hyperparameters α and β, which we set to fixed constants (1, 19). The use of a Beta prior distribution for a Bernoulli random variable is standard practice in Bayesian modeling due to mathematical convenience and the interpretability of the hyperparameters as effective counts [27].

We now turn to true question value F_i and observed input D_i. First, $P(F_i \mid \ldots)$ is still defined as in Section 4, maintaining as before the multivariate relationships between questions. Second, the user question response D_i is modeled as being drawn from either the true answer F_i or the error distribution θ_i, depending on whether a mistake is made according to R_i:

$$D_i \mid F_i, \theta_i, R_i \sim \begin{cases} \text{PointMass}(F_i) & \text{if } R_i = 0, \\ \text{Discrete}(\theta_i) & \text{otherwise,} \end{cases} \tag{9}$$

If $R_i = 0$, no error occurs and the data entry worker inputs the correct value for D_i, and thus $F_i = D_i$. Probabilistically, this means D_i's probability is concentrated around F_i (i.e., a point mass at F_i). However, if $R_i = 1$, then the data entry worker makes a mistake, and instead chooses a response for the question from the error distribution. Again, this error distribution is a discrete distribution over possible question responses parameterized by the fixed parameters θ_i, which we set to be the uniform distribution in our current model.[6]

6.2 Error Model Inference

The ultimate variable of interest in the error model is R_i: we wish to induce the probability of making an error for each previously answered question, given the actual question responses that are currently available:

$$P(R_i \mid \mathbf{D} = \mathbf{d}), \tag{10}$$

where $\mathbf{D} = \{F_1, \ldots, F_\ell\}$ are the fields that currently have responses, the values of which are $\mathbf{d} = \{f_1, \ldots, f_\ell\}$ respectively. This probability represents a contextualized error likelihood due to its dependence on other field values through the Bayesian network.

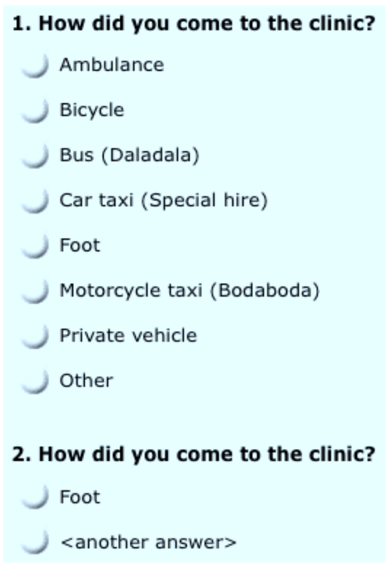
Again, we can use standard Bayesian inference procedures to compute this probability. These procedures are black-box algorithms whose technical descriptions are beyond the scope of this paper. We refer the reader to standard graphical model texts for an in-depth review of different techniques [25], [28]. In our implementation, we use the Infer.NET toolkit [22] with the Expectation Propagation algorithm [29] for this estimation.

6.3 Deciding when to Re-ask

Once we have inferred a probability of error for each question, we can choose to perform re-asking either during entry, where the error model is consulted after each response, or after entry, where the error model is consulted once with all form responses, or both.

5. Note that in a hierarchical Bayesian formulation such as ours, random variables can represent not just specific values but also parameters of distributions. Here, θ_i is the parameters of the error distribution.

6. A more precise error distribution would allow the model to be especially wary of common mistakes. However, learning such a distribution is itself a large undertaking involving carefully designed user studies with a variety of input widgets, form layouts, and other interface variations, and a post-hoc labeling of data for errors. This is another area for future work.


1. How did you come to the clinic?

- Ambulance
- Bicycle
- Bus (Daladala)
- Car taxi (Special hire)
- Foot
- Motorcycle taxi (Bodaboda)
- Private vehicle
- Other

2. How did you come to the clinic?

- Foot
- <another answer>

Fig. 6. An example of a reformulated question.

The advantage of integrating re-asking into the primary entry process is that errors can be caught as they occur, when the particular question being entered is still recent in the data entry worker's attention. The cognitive cost of re-entering a response at this point is lower than if that question were re-asked later. However, these error likelihood calculations are made on the basis of incomplete information — a question response may at first appear erroneous *per se*, but when viewed in the context of concordant responses from the same instance may appear less suspicious. In contrast, by batching re-asking at the end of a form instance, USHER can make a holistic judgment about the error likelihoods of each response, improving its ability to estimate error. This tradeoff reveals an underlying human-computer interaction question about how recency affects ease and accuracy of question response, a full exploration of which is beyond the scope of this paper.

To decide whether to re-ask an individual question, we need to consider the tradeoff between improved data quality and the cost of additional time required for re-asking. USHER allows the form designer to set an error probability threshold for re-asking. When that threshold is exceeded for a question, USHER will re-ask that question, up to a predefined budget of re-asks for the entire form instance. If the response to the re-asked question differs from the original response, the question is flagged for further manual reconciliation, as in double entry. For in-flight re-asking, we must also choose either the original or re-asked response for this field for further predictions of error probabilities in the same form instance. We choose the value that has the lesser error probability, since in the absence of further disambiguating information that value is more likely to be correct according to the model.

7 QUESTION REFORMULATION

Our next application of USHER's probabilistic formalism is *question reformulation*. To reformulate a question means to simplify it in a way that reduces the chances of the data entry worker making an error. Figure 6 presents an example of a question as originally presented and a reformulated version thereof. Assuming that the correct response is *Foot*, the data entry worker would only need to select it out of two rather than eight choices, reducing the chance of making a mistake. Moreover, reformulation can enable streamlining of the input interface, improving data entry throughput.

In this work we consider a constrained range of reformulation types, emphasizing an exploration of the *decision* to reformulate rather than the interface details of the reformulation itself. Specifically, our target reformulations are binary questions confirming whether a particular response is the correct response, such as in the example. If the response to the binary question is negative, then we ask again the original, non-reformulated question. We emphasize that the same basic data-driven approach described here can be applied to more complex types of reformulation, for instance, formulating to k values where $k < D$, the size of the original answer domain.

The benefits of question reformulation rely on the observation that different ways of presenting a question will result in different error rates. This assumption is borne out by research in the HCI literature. For example, in recent work Wobbrock et al. [30] showed that users' chances of clicking an incorrect location increases with how far and small the target location is. As a data entry worker is presented with more options to select from, they will tend to make more mistakes. We also note that it takes less time for a data entry worker to select from fewer rather than more choices, due to reduced cognitive load and shorter movement distances. These findings match our intuitions about question formulation — as complexity increases, response time and errors increase as well.

However, question reformulation comes with a price as well. Since reformulating a question reduces the number of possible responses presented to the data entry worker, it is impossible for the reformulated question to capture all possible legitimate responses. In the example above, if *Foot* was not the correct response, then the original question would have to be asked again to reach a conclusive answer. Thus, the decision to reformulate should rest on how *confident* we are about getting the reformulation "right" — in other words, the probability of the most likely answer as predicted by a probabilistic mechanism.

In light of the need for a probabilistic understanding of the responses, USHER's reformulation decisions are driven by the underlying Bayesian network. We consider reformulation in three separate contexts: *static reformulation*, which occurs during the form layout process; *dynamic reformulation*, which occurs while responses are being entered; and *post-entry reformulation*, which is applied in conjunction with re-asking to provide another form of cross-validation for question responses.

7.1 Static Reformulation

In the static case, we decide during the design of a form layout which questions to reformulate, if any, in conjunction with the question ordering prediction from Section 5. This form of reformulation simplifies questions that tend to have predominant responses across previous form instances. Static reformulation is primarily appropriate for situations when forms are printed on paper and question ordering is fixed. Standard practice in form design is to include *skip-logic*, a notation to skip the full-version of the question should the answer to the reformulated question be true. Alternatively, false responses to reformulated questions can be compiled and subsequently re-asked after the standard form instance is completed.

For each question, we decide whether to reformulate on the basis of the probability of its *expected response*. If that response exceeds a tunable threshold, then we choose to reformulate the question into its binary form. Formally, we reformulate when

$$\max_j P(F_i = f_j) \geq T_i, \tag{11}$$

where T_i is the threshold for question i. In this work we consider values of T_i that are fixed for an entire form, though in general it could be adjusted on the basis of the original question's complexity or susceptibility to erroneous responses. We note that this reformulation mechanism is directly applicable for questions with discrete answers, either categorical (e.g., *blood-type*) or ordinal (e.g., *age*); truly continuous values (e.g., *weight*) must be discretized before reformulation. However, continuous questions with large answer domain cardinalities are less likely to trigger reformulation, especially if their probability distributions are fairly uniform.

Setting the threshold T provides a mechanism for trading off improvements in data quality with the potential drawback of having to re-ask more questions. At one extreme, we can choose to never reformulate; at the other, if we set a low threshold we would provide simplified versions of every question, at the cost of doubling the number of questions asked in the worst-case.

7.2 Dynamic Reformulation

Paralleling the dynamic approach we developed for question ordering (Section 5.1), we can also decide to reformulate questions during form entry, making the decision based on previous responses. The advantage of dynamic reformulation is that it has the flexibility to change a question based on context – as a simple example, conditioned on the answer for an *age* question being 12, we may choose to reformulate a question about *occupation* into a binary *is-student* question. Dynamic reformulation is appropriate in many electronic, non-paper based workflows. In this case, the reformulation decision is based on a *conditional expected response*; for question i we reformulate when

$$\max_j P(F_i = f_j \mid \mathbf{G} = \mathbf{g}) \geq T_i, \tag{12}$$

where previous questions $\mathbf{G} = \{F_1, \ldots, F_\ell\}$ have already been filled in with values $\mathbf{g} = \{f_1, \ldots, f_\ell\}$. Note the similarities in how the objective function is modified for both ordering and reformulation (compare equations 11 and 12 to equations 4 and 6).

7.3 Reformulation for Re-asking

Finally, another application of reformulation is for re-asking questions. As discussed in Section 6, the purpose of re-asking is to identify when a response may be in error, either during or after the primary entry of a form instance. One way of reducing the overhead associated with re-asking is to simplify the re-asked questions. Observe that a re-ask question does not have to illicit the true answer, but rather a corroborating answer. For example, for the question *age*, a reformulated re-ask question could be the discretization bucket in which the age falls (e.g., *21–30*). From the traditional data quality assurance perspective, this technique enables dynamic cross-validation questions based on contextualized error likelihood.

The actual mechanics of the reformulation process are the same as before. Unlike the other applications of reformulation, however, here we have an answer for which we can compute error likelihood.

8 Evaluation

We evaluated the benefits of USHER by simulating two data entry scenarios to show how our system can improve data quality. We focused our evaluation on the quality of our model and its predictions. While we believe that the data entry user interface can also benefit from value prediction, as we discuss in Section 9, we factor out the human-computer interaction concerns of form widget design by automatically simulating user entry. As such, we set up experiments to measure our models' ability to predict users' intended answers, to catch artificially injected errors, and to reduce error using reformulated questions. We first describe the experimental data sets, and then present our simulation experiments and results.

8.1 Data Sets and Experimental Setup

We examine the benefits of USHER's design using two data sets, previously described in Section 3. The *survey* data set comprises responses from a 1986 poll about race and politics in the San Francisco-Oakland metropolitan area [31]. The UC Berkeley Survey Research Center interviewed 1,113 persons by random-digit telephone dialing. The *patient* data set was collected from anonymized patient intake records at a rural HIV/AIDS clinic in Tanzania. In total we had fifteen questions for the survey and nine for the patient data. We discretized continuous values using fixed-length intervals and treated the absence of a response to a question as a separate value to be predicted.

For both data sets, we randomly divided the available prior submissions into *training* and *test* sets, split 80% to 20%, respectively. For the survey, we had 891 training instances and 222 test; for patients, 1,320 training and 330 test. We performed structure learning and parameter estimation using the training set. As described in Section 4, this resulted in the graphical models shown in Figures 1 and 2. The test portion of each dataset was then used for the data entry scenarios presented below.

In our simulation experiments, we aim to verify hypotheses regarding three components of our system: first, that our data-driven question orderings ask the most uncertain questions first, improving our ability to predict missing responses; second, that our re-asking model is able to identify erroneous responses accurately, so that we can target those questions for verification; and third, that question reformulation is an effective mechanism for trading off between improved data quality and user effort.

8.2 Ordering

For the ordering experiment, we posit a scenario where the data entry worker is interrupted while entering a form submission, and thus is unable to complete the entire instance. Our goal is to measure how well we can predict those remaining questions under four different question orderings: USHER's pre-computed static ordering, USHER's dynamic ordering (where the order can be adjusted in response to individual question responses), the original form designer's ordering, and a random ordering. In each case, predictions are made by computing the maximum position (mode) of the probability distribution over un-entered questions, given the known responses. Results are averaged over each instance in the test set.

The left-hand graphs of Figure 7 measure the average number of correctly predicted unfilled questions, as a function of how many responses the data entry worker entered before being interrupted. In each case, the USHER orderings are able to predict question responses with greater accuracy than both the original form ordering and a random ordering for most truncation points. Similar relative performance is exhibited when we measure the percentage of test set instances where *all* unfilled questions are predicted correctly, as shown in the right side of Figure 7.

The original form orderings tend to underperform their USHER counterparts. Human form designers typically do not optimize for asking the most difficult questions first, instead often focusing on boilerplate material at the beginning of a form. Such design methodology does not optimize for greedy information gain.

As expected, between the two USHER approaches, the dynamic ordering yields slightly greater predictive power than the static ordering. Because the dynamic approach is able to adapt the form to the data being entered, it can focus its question selection on high-uncertainty questions specific to the current form instance. In contrast, the static approach effectively averages over all possible uncertainty paths.

8.2.1 Re-asking

For the re-asking experiment, our hypothetical scenario is one where the data entry worker enters a complete form instance, but with erroneous values for some question responses.[7] Specifically, we assume that for each data value the data entry worker has some fixed chance p of making a mistake. When a mistake occurs, we assume that an erroneous value is chosen uniformly at random. Once the entire instance is entered, we feed the entered values to our error model and compute the probability of error for each question. We then re-ask the questions with the highest error probabilities, and measure whether we chose to re-ask the questions that were actually wrong. Results are averaged over 10 random trials for each test set instance.

Figure 8 plots the percentage of instances where we chose to re-ask all of the erroneous questions, as a function of the number of questions that are re-asked, for error probabilities of 0.05, 0.1, and 0.2. In each case, our error model is able to make significantly better choices about which questions to re-ask than a random baseline. In fact, for $p = 0.05$, which is a representative error rate that is observed in the field [7], USHER successfully re-asks all errors over 80% of the time within the first three questions in both data sets. We observe that the traditional approach of double entry corresponds to re-asking every question; under reasonable assumptions about the occurrence of errors, our model is able to achieve the same result of identifying all erroneous responses at a substantially reduced cost.

8.2.2 Reformulation

For the reformulation experiment, we simulate form filling with a background error rate and time cost in order to evaluate the impact of reformulated questions. During simulated entry, when a possible response a is at the mode position of the conditional probability distribution and has a likelihood greater than a threshold t, we ask whether the answer is a as a reformulated binary question. If a is not the true answer, we must re-ask the full question. Results are averaged over each instance in the test set.

Before discussing these results, we motivate the choice of error rates and costs functions that we employ in this experiment. As mentioned in Section 7, the intuition behind question reformulation is grounded in prior literature, specifically the notion that simpler questions enjoy both lower error rate and user effort. However, the downside with reformulation is that entry forms may cost more to complete, due to reformulated questions with negative responses.

In order to bootstrap this experiment, we need to derive a representative set of error rates and entry costs that vary with the complexity of a question. Previous work [30], [32] has shown that both entry time and error rate increase as a function of interface complexity. In particular, Fitts' Law [32] describes the time complexity of interface usage via an *index of complexity* (ID), measured in *bits* as $\log(A/W + 1)$. This is a logarithmic function of the ratio between target size W and target distance A. Mapping this to some typical data entry widgets such as radio-buttons and drop-down menus, where W is fixed and A increases linearly with the number of selections, we model time cost as $\log(D)$ where D is the domain cardinality of the answer. In other words, time cost grows with how many bits it takes to encode the answer. For our experiments, we set the endpoints at 2 seconds for $D = 2$ up to 4 seconds for $D = 128$.

We also increase error probabilities logarithmically as a function of domain cardinality D, relying on the intuition that error will also tend to increase as complexity increases [30]. Our error rates vary from 1% for $D = 2$ to 5% for $D = 128$.

7. Our experiments here do not include simulations with in-flight re-asking, as quantifying the benefit of re-asking during entry – question recency — is a substantial human factors research question that is left as future work.

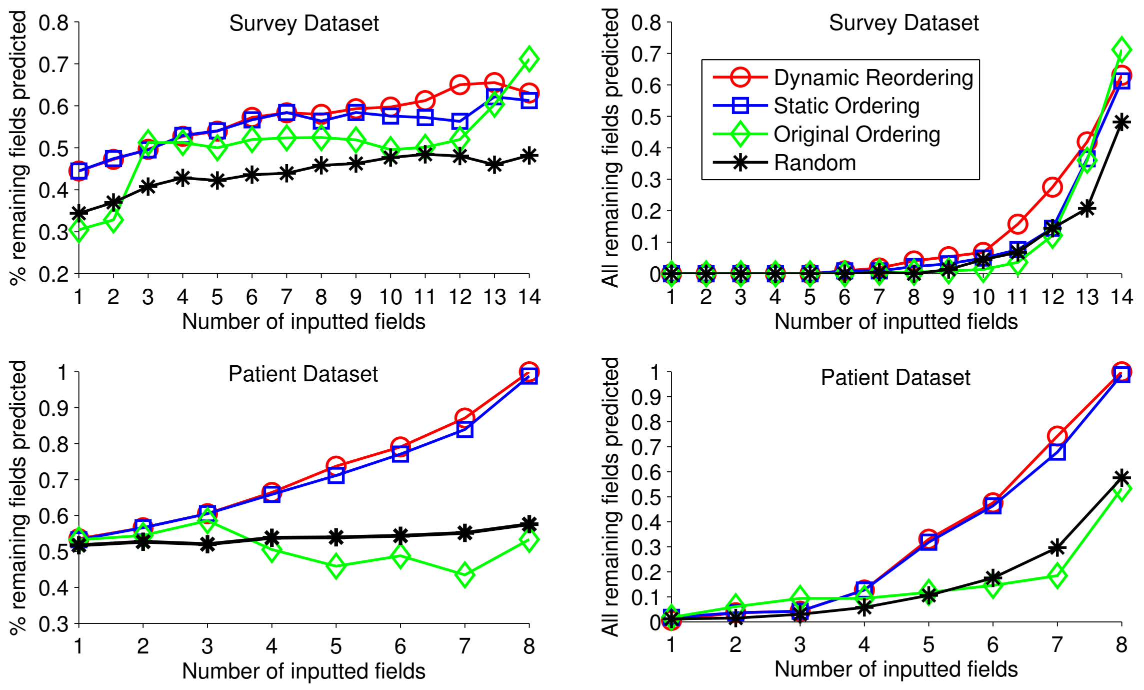


Fig. 7. Results of the ordering simulation experiment. In each case, the *x*-axis measures how many questions are filled before the submission is truncated. In the charts on the left side, the *y*-axis plots the average proportion of remaining question whose responses are predicted correctly. In the charts on the right side, the *y*-axis plots the proportion of form instances for which *all* remaining questions are predicted correctly. Results for the survey data are shown at top, and for the HIV/AIDS data at bottom.

We do not claim the generalizability of these specific numbers, which are derived from a set of strong assumptions. Rather, the values we have selected are representative for studying the general trends of the tradeoff between data quality and cost that re-asking enables, and are in line with typical values observed in the field [7]. Furthermore, we attempted this experiment with other error and cost parameters and found similar results.

The results of question reformulation can be found in Figure 9. In the pair of graphs entitled A, we measure the error rate over reformulation thresholds for each dataset. Our results confirm the hypothesis that the greater the number of additional reformulated questions we ask, the lower the error rate. In the pair of graphs entitled B, we observe that as the selectivity (threshold) of reformulation goes up, the likelihood that we pick the correct answer in reformulation also rises. Observe that reformulation accuracy is greater than 80% and 95% for the *survey* and *patient* datasets, respectively, at a threshold of 0.8. In the pair of graphs entitled C, we see an unexpected result: entry with reformulation features a time cost that quickly converges with, and in the case of the *patient* dataset, dips below that of standard entry, at thresholds beyond 0.6. Finally, in the pair of graphs entitled D, we summarize the time cost incurred by additional questions versus the time savings of the simpler reformulated questions. Of course, given our assumptions, we cannot make a strong conclusion about the cost of question reformulation. Rather, the important takeaway is that the decrease in effort won by correct reformulations can help to offset the increase due to incorrect reformulations.

9 Discussion: Dynamic Interfaces for Data Entry

In the sections above, we described how USHER uses statistical information traditionally associated with offline data cleaning to improve interactive data entry via question ordering and re-asking. This raises questions about the human-computer interactions inherent in electronic form-filling, which are typically device- and application-dependent. In one application, we are interested in how data quality interactions play out on mobile devices in developing countries, as in the Tanzanian patient forms we examined above. Similar questions arise in traditional online forms like web surveys. In this section we outline some design opportunities that arise from the probabilistic power of the models and algorithms in USHER. We leave the investigation of specific interface designs and their evaluation in various contexts to future work.

While an interactive USHER-based interface is presenting questions (either one-by-one or in groups), it can infer a probability for each possible answer to the next question; those probabilities are contextualized (conditioned) by previous responses. The resulting quantitative probabilities can be exposed to users in different manners and at different times. We present some of these design options in the following:

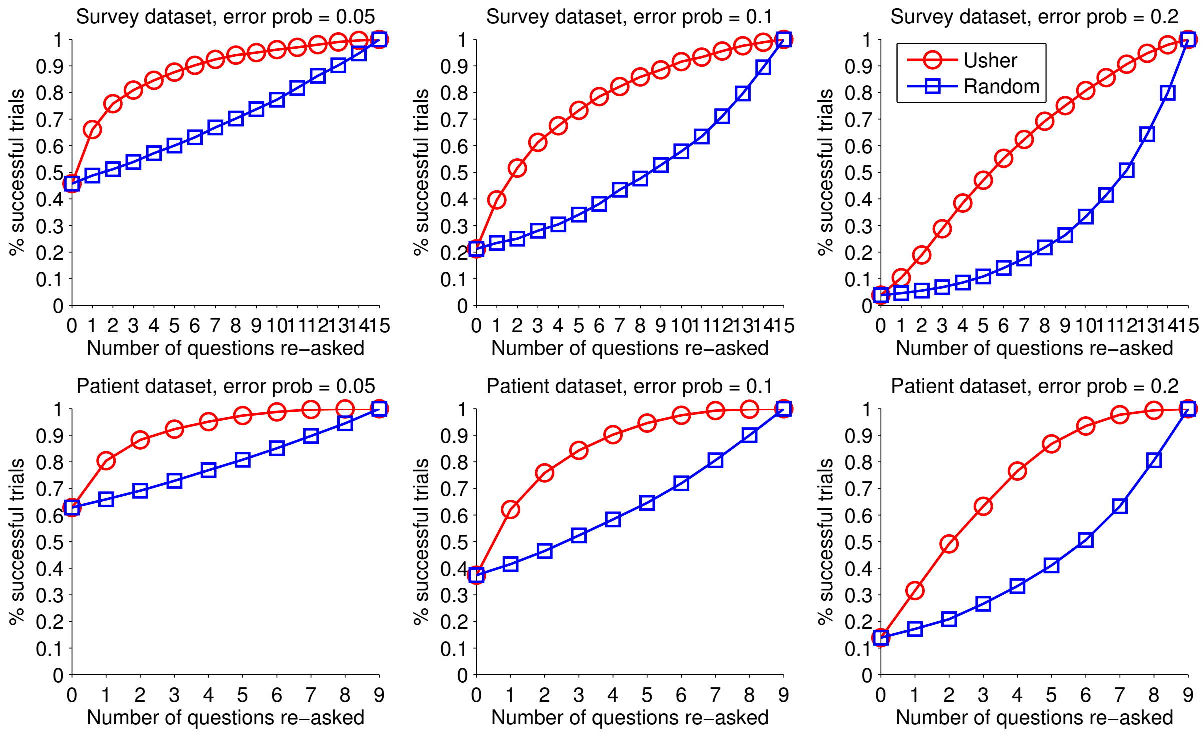


Fig. 8. Results of the re-asking simulation experiment. In each case, the x-axis measures how many questions we are allowed to re-ask, and the y-axis measures whether we correctly identify all erroneous questions within that number of re-asks. The error probability indicates the rate at which we simulate errors in the original data. Results for the survey data are shown at top, and for the HIV/AIDS data at bottom.

1) **Time of exposure: pre- and post-entry.** Before entry, Usher's probabilistic model can be used to improve data entry speed by adjusting the *friction* of entering different answers: likely results can be made easy or attractive to enter, while unlikely results can be made to require more work. One example of this is the previously described reformulation technique. Additional examples of data-driven variance in friction include type-ahead mechanisms in textfields, "popular choice" items repeated at the top of drop-down lists, and direct decoration (e.g., coloring or font-size) of each choice in accordance with its probability. A downside of beforehand exposure of answer probabilities is the potential to bias answers. Alternatively, probabilities may be exposed in the interface only *after* the user selects an answer. This becomes a form of *assessment* — for example, by flagging unlikely choices as potential outliers. This can be seen as a soft, probabilistic version of the constraint violation visualizations commonly found in web forms (e.g., the red star that often shows up next to forbidden or missing entries). Post hoc assessment arguably has less of a biasing effect than friction. This is both because users choose initial answers without knowledge of the model's predictions, and because users may be less likely to modify previous answers than change their minds before entry.
2) **Explicitness of exposure:** Feedback mechanisms in adaptive interfaces vary in terms of how explicitly they intervene in the user's task. Adaptations can be considered *elective* versus *mandatory*. For instance, a drop-down menu with items sorted based on likelihood is mandatory with a high level of friction; whereas, a "split" drop-down menu, as mentioned above, is elective — the user can choose to ignore the popular choices. Another important consideration is the cognitive complexity of the feedback. For instance, when encoding expected values into a set of radio buttons, we can directly show the numeric probability of each choice, forcing a user to interpret these discrete probabilities. Alternatively, we can scale the opacity of answer labels — giving the user an indication of relative salience, without the need for interpretation. Even more subtly, we can dynamically adjust the size of answer labels' clickable regions — similar to the adjustments made by the iPhone's soft keyboard in response to the likelihood of various letters.
3) **Contextualization of interface:** Usher uses conditional probabilities to assess the likelihood of subsequent answers. However, this is not necessarily intuitive to a user. For example, consider a question asking for *favorite beverage*, where the most likely answers shown are *milk* and *apple juice*. This might be surprising in the abstract, but would be less so in a case where a previous question had identified the *age* of the person in question

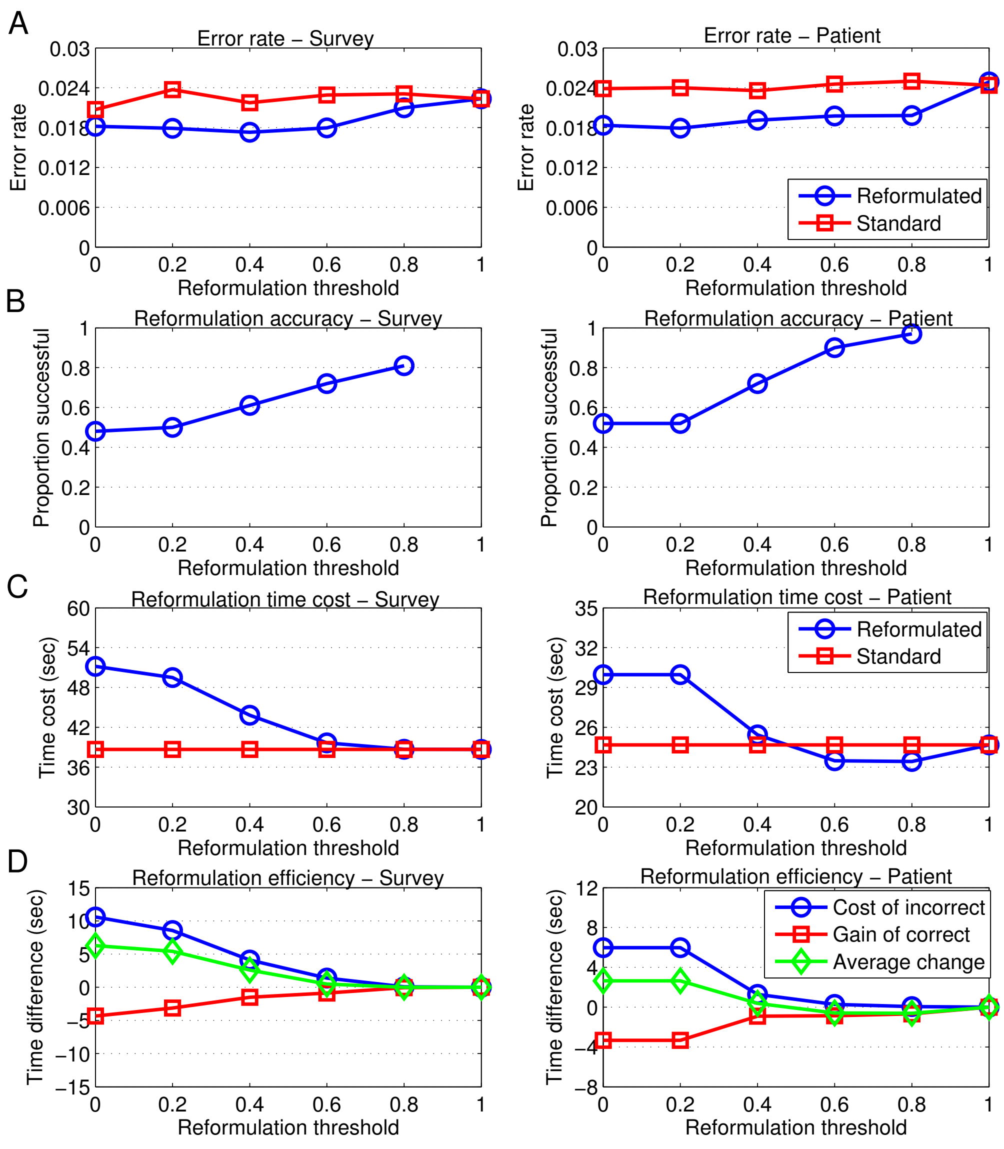


Fig. 9. Results of the question reformulation experiment. In each chart, the x-axis shows the reformulation thresholds; when the threshold = 1, no question is reformulated. *A* shows the overall error rate between reformulated and standard entry. *B* shows the likelihood that a reformulated answer was, in fact, the correct answer. *C* shows the impact of reformulation on user effort, measured as time — average number of seconds per form. *D* shows the gain/loss in effort due to when reformulation is correct vs incorrect.

to be *under 5 years old*. The way that the interface communicates the context of the current probabilities is an interesting design consideration. For example, "type-ahead" text interfaces have this flavor, showing the likely suffix of a word contextualized by the previously-entered prefix. More generally, USHER makes it possible to show a history of already-entered answers that correlate highly with the value at hand.

Note that these design discussions are not specifically tied to any particular widgets. In Figure 10 we show some examples of user interface widgets that have been adapted using information provided by USHER's probabilistic model: the drop-down menu in part A features first an *elective* split-menu adaptation before entry and a color-encoded value *assessment* after entry; the textfield in part B shows type-ahead suggestions ordered by likelihood, thus decreasing the physical distance (a form of friction) for more-likely values; the radio buttons in part C directly communicate probabilities to the user.

While these broad design properties help clarify the potential user experience benefits of USHER's data-driven philoso-

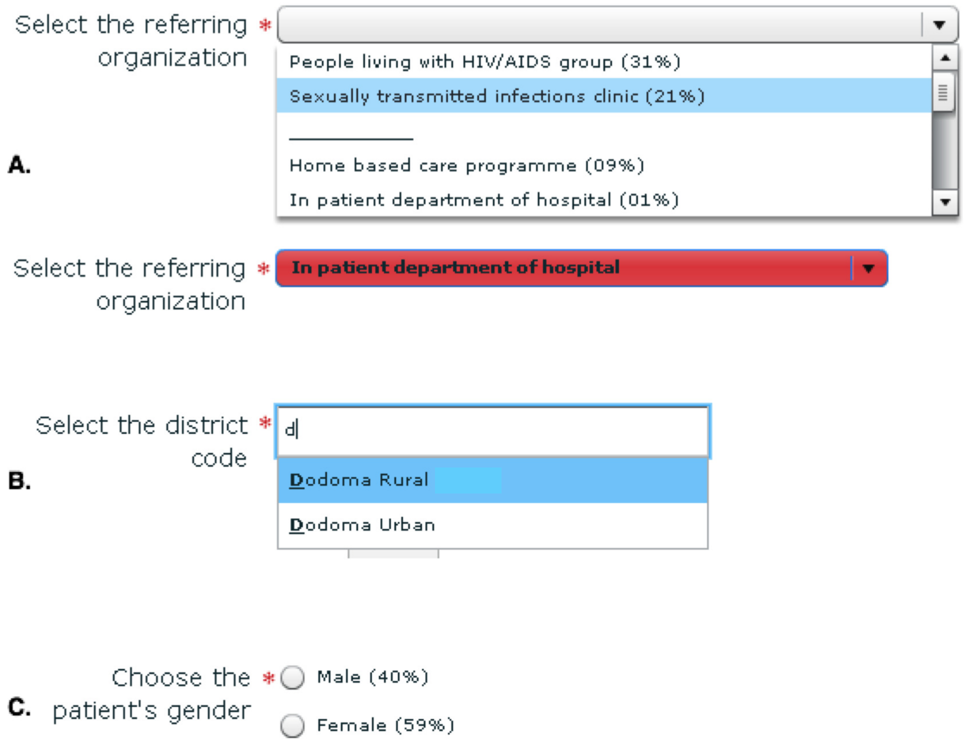

Select the referring organization *
People living with HIV/AIDS group (31%)
Sexually transmitted infections clinic (21%)
Home based care programme (09%)
In patient department of hospital (01%)
A.
Select the referring organization *
In patient department of hospital
Select the district code *
d
Dodoma Rural
Dodoma Urban
B.
Choose the patient's gender *
Male (40%)
Female (59%)
C.

Fig. 10. Mockups of some simple dynamic data entry widgets illustrating various design options.

phy, there are clearly many remaining questions about how to do this embedding effectively for different settings and users. Those questions are beyond the scope of this paper. In separate work, we used Ushers predictive ability to design intelligent user interface adaptations, studied them with data entry clerks in a rural Ugandan health clinic, and show that our our adaptations have the potential to reduce error (by up to 78%) [33].

10 Discussion and Future Work

In this paper, we have shown that a probabilistic approach can be used to design intelligent data entry forms that promote high data quality. USHER leverages data-driven insights to automate multiple steps in the data entry pipeline. Before entry, we find an ordering of form fields that promotes rapid information capture, driven by a greedy information gain principle, and can statically reformulate questions to promote more accurate responses. During entry, we dynamically adapt the form based on entered values, facilitating re-asking, reformulation, and real-time interface feedback in the sprit of providing appropriate entry friction. After entry, we automatically identify possibly erroneous inputs, guided by contextualized error likelihoods, and re-ask those questions, possibly reformulated, to verify their correctness. Our simulated empirical evaluations demonstrate the data quality benefits of each of these components: question ordering, reformulation and re-asking.

The USHER system we have presented is a cohesive synthesis of several disparate approaches to improving data quality for data entry. The three major components of the system — ordering, re-asking, and reformulation — can all be applied under various guises before, during, and after data entry. This suggests a principled roadmap for future research in data entry. For example, one combination we have not explored here is re-asking before entry. At first glance this may appear strange, but in fact that is essentially the role that cross-validation questions in paper forms serve, as pre-emptive reformulated re-asked questions. Translating such static cross-validation questions to dynamic forms is a potential direction of future work.

Another major piece of future work alluded to in Section 9 is to study how our probabilistic model can inform effective adaptations of the user interface during data entry. We intend to answer this problem in greater depth through user studies and field deployments of our system.

We can also extend this work by enriching the underlying probabilistic formalism. Our current probabilistic approach assumes that every question is discrete and takes on a series of unrelated values. Relaxing these assumptions would make for a potentially more accurate predictive model for many domains. Additionally, we would want to consider models that reflect temporal changes in the underlying data. Our present error model makes strong assumptions both about how errors are distributed and what errors look like. On that front, an interesting line of future work would be to learn a model of data entry errors and adapt our system to catch them.

Finally, we are in the process of measuring the practical impact of our system, by piloting USHER with our field partners, the United Nations Development Program's Millennium Villages Project [34] in Uganda, and a community health care program in Tanzania. These organizations' data quality concerns were the original motivation for this work and thus serve as an important litmus test for our system.

ACKNOWLEDGMENTS

The authors thank Maneesh Agrawala, Yaw Anokwa, Michael Bernstein, S.R.K. Branavan, Tyson Condie, Heather Dolan, Jeff Heer, Max van Kleek, Neal Lesh, Alice Lin, Jamie Lockwood, Bob McCarthy, Tom Piazza, Christine Robson and the anonymous reviewers for their helpful comments and suggestions. We acknowledge the Yahoo Labs Technology for Good Fellowship, the Natural Sciences and Engineering Research Council of Canada, the National Science Foundation Graduate Fellowship, and NSF Grant 0713661.

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