
Abstract
Policy specification for personal user data is a hard problem, as it depends on many factors that cannot be predetermined by system developers. Simultaneously, systems are increasingly relying on users to make security decisions. In this paper, we propose the approach of Policy by Example (PyBE) for specifying user-specific security policies. PyBE brings the benefits of the successful approach of programming by example (PBE) for program synthesis to the policy specification domain. In PyBE, users provide policy examples that specify if actions should be allowed or denied in certain scenarios. PyBE then predicts policy decisions for new scenarios. A key aspect of PyBE is its use of active learning to enable users to correct potential errors in their policy specification. To evaluate PyBE’s effectiveness, we perform a feasibility study with expert users. Our study demonstrates that PyBE correctly predicts policies with 76% accuracy across all users, a significant improvement over naive approaches. Finally, we investigate the causes of inaccurate predictions to motivate directions for future research in this promising new domain.

1 Introduction
In the era of pervasive computing, the security of user data and resources is of paramount importance. Complex systems such as IoT platforms (e.g., IFTTT [51] and SmartThings [41]), smartphone platforms (e.g., Android and iOS) and even traditional commodity platforms are being leveraged for processing user data. However, our knowledge of policy specification has not kept pace with the rise of complex systems that are increasingly relying on the user to specify the security policy.

Further, user data has become increasingly user-specific. Users no longer directly deal with generic files, but create specific data objects such as notes, whiteboard snapshots, and selfies. This data is abstract, i.e., its importance and properties are subjective. System designers or application developers cannot specify a security policy for abstract user data. The situation is even critical for novel security systems that provide strong data security guarantees for user data (e.g., decentralized information flow control (DIFC) systems for Android [19,32,33,54], Chromium [5]). Such systems are impractical to deploy unless users specify security policies; and users are bad at specifying security policies [29,40] without assistance.

This paper raises the simple but important question of policy specification: how to teach the system what the user wants to protect, and how the user wants to protect it? Consider the following example: a smartphone user wants to synchronize all personal notes with her cloud account, except notes labeled as medical data. Since we are dealing with user-specific data-use scenarios, we can justifiably expect the user to provide some input to the system. However, expecting the user to enumerate every possible scenario involving medical data is impractical. The policy must be predicted.

We propose the approach of specifying Policy by Example (PyBE) for user-specific data. PyBE is inspired by the successful use of programming by example (PBE) for program synthesis. Specifically, we emulate the approach of Gulwani [14], where the user specifies examples consisting of the input and output, and the system learns a program that can predict the output for unknown (but similar) inputs. Similarly, in PyBE, the user specifies policy examples, in terms of the data-use scenario (i.e., the input) and the policy decision (i.e., the output). The system uses the policy examples to predict policy decisions for new scenarios. By requiring only relevant examples, and not complete policy specification, PyBE makes policy specification tractable.

Predicting security policies for abstract, user-specific data with unknown properties is hard, as the learner cannot make any assumptions about the input data points. In contrast, prior work on predicting privacy policies for well-known private data [8,23] can make assumptions that aid prediction; e.g., Cranshaw et al. [8] take
advantage of probabilistic models to learn location privacy policies knowing that location and time are continuous variables. PyBE cannot make any such assumptions, which puts us at a significant disadvantage. However, this disadvantage drove us to embrace a simpler approach that does not demand specific properties from data.

We chose a variant of the \( k \) nearest neighbor (\( k \text{NN} \)) classifier \[31\] for predicting policies. Our key requirements were that the algorithm be (1) non-parametric, i.e., independent of models that rely on fixed set of parameters, and (2) easy to explain, i.e., for the user to understand how the policy was inferred. Recall that a policy example is composed of a scenario and the corresponding policy decision. To predict the policy decision for a new scenario, our algorithm performs a nearest neighbor search for finding similar scenarios from the user’s examples, and predicts the majority policy decision.

An important challenge in applying \( k \text{NN} \) is calculating the distance between data points. To calculate distance between scenarios, we treat scenarios as Boolean functions, and propose a novel distance metric for the same. As some policies may be relatively more important to the user, we extend our metric to support weights. Note that existing distance metrics (e.g., \( \text{jaccard} \) distance) may require significant re-engineering to incorporate weights, which motivates our development of a new metric.

PyBE recognizes that policy specification by users in any form is error prone. A key contribution is our use of active learning for enabling the user to correct policy decisions. We draw inspiration from the work of Gulwani \[14\], which detects noise in the user’s examples, and prompts the user for new outputs for problematic examples. Similarly, PyBE uses noise in the user’s policy examples as an indication of error in policy decisions, and engage the user in correcting errors.

We evaluate the feasibility of PyBE with a study of expert users. Our study involves 8 participants, and 5 target security policies (e.g., exporting to the enterprise cloud), i.e., we solve 40 independent policy specification problems. Our participants generate 246 policy scenarios in total, and assign decisions for the 5 policies, resulting in a total of 1,230 policy examples across participants.

We perform two experiments with this data. First, we find errors in policy decisions using a manual review and a PyBE-assisted interactive review of policy examples. Then, we test PyBE’s prediction for randomly generated scenarios with unknown policy decisions. PyBE demonstrates a prediction accuracy of over 76% across all participants, and fares better than our assumed baseline of a random coin flip, and a naive approach. A significant finding is that the PyBE-assisted interactive review approach helped participants find five times as many errors as their manual reviews.

Our evaluation is evidence of the feasibility, i.e., the effectiveness of PyBE in terms of both prediction accuracy and error identification, but does not speak to the general usability of PyBE. Although 8 participants is small for a human study, the evaluation is able to answer important questions through the analysis of user-generated policy examples (i.e., 1,230 user-generated examples). The research questions answered in the evaluation operate at the level of policy examples, making the dataset sufficiently large for evaluating feasibility.

The contributions of this paper are as follows:

- We introduce the Policy by Example (PyBE) paradigm for predicting user-specific security policies. Our approach takes labeled policy scenarios from the user, and predicts policy decisions for new policy scenarios.
- We use an interactive approach to assist users in finding incorrect policy decisions in their examples. We empirically demonstrate its effectiveness over manual policy reviews.
- We perform a feasibility study with expert users, and demonstrate better prediction accuracy than both a baseline as well as a naive approach.

This paper is the first step in our vision of a policy assistant for user data. With PyBE, we provide an approach for predicting security policies for user-specific data, and demonstrate its technical feasibility. Further, we analyze our incorrect predictions, and describe the lessons we learned in the process. Finally, we describe challenges (e.g., usability for non-experts, modeling policy change) and future research directions in this promising new area.

## 2 Related Work

The notion of Policy by Example (PyBE) is inspired by recent work in the domain of Programming by Example (PBE). The objective of PBE is simple: if the user knows the steps for performing a task, the user should not have to write a program; instead, the computer should learn from the user’s actions on an example, and generalize the program \[9, 26\]. However, the user may not always be able to express the reasoning, or the intermediate steps, involved in creating a program. Recent work by Gulwani \[14\] makes PBE feasible for such programming tasks, by using only input-output examples to synthesize a program that predicts outputs for unseen inputs. PyBE follows a similar intuition, and predicts policy decisions for new scenarios using only input-output examples (i.e., policy scenarios and corresponding decisions).

However, PyBE does not generalize the program before testing, as is often done in PBE. That is, while the proposed paradigm is conceptually similar to PBE, the process used to predict policies borrows from another well-established domain: case-based reasoning.
(CBR) [25]. In CBR, the outcome of a test case is determined by looking at the outcomes of previously observed cases (e.g., legal reasoning using precedents). In a way, CBR mimics a human expert’s reasoning, and performs lazy generalization of domain knowledge at testing time. CBR has been successfully used in many domains, e.g., synthesizing music [1, 2], providing decision support in molecular biology [22], and for solving spatial reasoning problems [17]. However, to our knowledge, CBR has never been used for predicting user security policies, and PyBE is novel in its use of a similarity heuristic (i.e., a form of CBR) for predicting security policies.

A critical advantage of CBR is that it provides a way to deal with uncertainty, in contrast with the process of eager learning (e.g., rule induction). Prior user-controllable methods for predicting privacy policies for well-known private data (e.g., Location) use eager learning, which requires making strategic parameter choices for generalization, often based on some known properties of the training data [8, 12, 23]. For example, Cranshaw et al. [8] use a probabilistic model to learn location privacy policies, assuming the availability of a large number of data points since location is a continuous variable. However, PyBE cannot make such assumptions for user data with uncertain properties (e.g., Bob’s scanned documents, Alice’s notes), and uses a form of CBR, which does not require a priori generalization.

Prior work has proposed usable interfaces for eliciting security responses, which are relevant for our long-term vision of creating a policy assistant for user data. For instance, a prototype of PyBE for a computing device may adopt the “interactive dropdowns” in Johnson et al.’s interactive policy authoring template for specifying initial examples [20, 21]. Similarly, Reeder et al.’s “expandable grids” may be adapted for visualizing policy examples for the user [37]. Such work only provides interfaces, and does not fulfill PyBE’s objective of making policy specification feasible through prediction. Further, recent work on user-driven access control (e.g., Roesner et al. [39], Ringer et al. [38]) provides a usable way of acquiring the user’s policy decision, by embedding access permissions into the user’s natural UI flow of accessing resources. However, defining specific permissions (i.e., gadgets) for an exponential space of subjective and user-specific data-use scenarios may be infeasible.

Prior work also complements the specification of user-specific policies, by providing content recognition for automatically tagging data for PyBE [6, 44, 48, 49, 52], or by providing security profiles for standard, well-known, security settings (e.g., Android permissions) [27, 28], allowing PyBE to focus on predicting policies for abstract, user-specific data.

Finally, while PyBE assists the user in specifying policies for user-specific data, there has been prior research in the domain of policy specification to help application or system developers. Prior work provides application developers with tools for expressing their security policies [10, 15, 16, 45]. Further, in contrast with prior work that assists developers in expressing known policies, Slankas et al. aid the developer by extracting access control rules from application-specific text artifacts using natural language processing (NLP) [45]. Similarly, access control logs and system call traces have previously been used to refine the system’s security policies (e.g., EASEAndroid [53] and Polgen [47]).

3 Motivation and Problem

User data and data-use scenarios are user-specific. External observers such as system designers or application developers cannot specify the user’s security policy without knowing the user’s context of data use [4, 34]. Moreover, this constraint is not limited to user-owned data; prior work demonstrates that even the security preferences for enterprise data vary with users and personal data-use contexts [13]. Consider the following example, which describes how two users may differ in terms of the relevance of data-use scenarios as well as security preferences for the same scenarios.

Example: Alice and Bob are two smartphone users, who use a fictional note-taking application Notes (similar to Google Keep) on their smartphones to collect and organize information. Notes backs up data to a designated cloud provider (e.g., Google Drive). Alice consolidates expenses by scanning paper receipts into the Notes application. However, Alice does not trust the cloud with medical data, and wants medical receipts (i.e., receipts scanned at the hospital) to only be stored locally, and not synced. Similarly, Bob uses Notes to aggregate his documents. As Notes is set up with Bob’s enterprise cloud, he does not wish to sync personal documents (e.g., documents created after work hours). That is, the requirements for what users want to protect (i.e., relevant data-use scenarios) are user-specific.

Further, even when two users may agree on what they want to protect, they may not agree on how they want to protect it. Suppose Alice and Bob meet at a conference and exchange business cards. Alice is self-employed, and feels confident in backing up business cards acquired after work hours to her enterprise cloud. However, Bob does not want to disclose networking opportunities to his company by syncing cards collected after work hours to his enterprise cloud. Security preferences for user data stem from the user’s personal circumstances.

Problem: In this paper, we focus on the problem of specifying user-specific security policies. The nature of the problem dictates that the policy specification must receive input from the user. However, it is impractical to expect the user to specify the policy for every scenario
in an exponential space. Hence, this paper addresses the problem of predicting the security policy for new data-use scenarios, based on the scenarios previously described by the user.

4 Policy by Example (PyBE)

PyBE is inspired by recent work on Programming by Examples [14], which learns a program from input-output examples. As shown in Figure 1a, the user provides policy examples (i.e., data-use scenarios and policy decisions), and PyBE interactively suggests corrections to the user’s policy decisions. PyBE then predicts policy decisions for new scenarios as shown in Figure 1b.

This section provides the intuition behind our approach. We describe PyBE formally in Section 5. We start by describing the structure of a policy example.

4.1 The Policy Example

A policy example is composed of a scenario, and a policy decision (i.e., allow/1 or deny/0) for that scenario. A scenario is as a set of tags, where each tag denotes the resource to be protected (e.g., business card) or a condition that influences the policy (e.g., created after work hours). Using a set of tags enables users to describe complex scenarios composed multiple conditions or data objects. Our use of tags is motivated by prior work that demonstrates that users can effectively re-purpose organizational tags to express access control policies [24].

In addition to the user-customizable policy example, we also define a fixed policy target which represents the action controlled by the policy; e.g., exporting data to the enterprise cloud, i.e., the WorkCloud policy target. Policy specification is performed separately for each policy target, i.e., independent of other targets. Thus, each target represents a separate high-level policy that must be specified (e.g., the user’s WorkCloud policy). The policy targets used in this paper are motivated by prior work on restricting the network export of secret data [5, 32, 50].

Table 1 shows Bob’s policy examples for the WorkCloud policy target. We describe each example, along with Bob’s security requirement behind it. First, Bob considers data created at home to be personal, so Bob’s photos created at home must never be exported to the enterprise cloud. Thus, Bob denies export for example 1, i.e., {Home, Photos}. Second, photos taken at work may be exported to the enterprise cloud. Hence, Bob allows export for example 2, i.e., {Work, Photos}. Third, Bob does not (currently) imagine a situation where he would deny export for documents. Hence, Bob allows export for example 3, i.e., {Document}. We use Bob’s examples to describe PyBE.

4.2 Our Approach

As described previously, PyBE uses a variation of the kNN algorithm for predicting policies. That is, Bob provides PyBE with a set of policy examples (i.e., scenarios labeled with policy decisions). When faced with a new scenario with an unknown policy decision, we perform a nearest neighbor search of Bob’s examples. That is, we search Bob’s examples for the closest examples, i.e., examples with scenarios closest to the new scenario, and predict the policy decision of the majority of the closest examples. Note that distance between examples is described in terms of their scenarios (i.e., when we say “examples are close”, it means their scenarios are close).

An approach for predicting security policies should be deterministic if we want users to understand its outcome (i.e., independent of arbitrary parameters). Based on this rationale, we eliminate the need to specify the parameter k. Our variation of kNN considers the closest neighbors as all neighbors at the closest distance, instead of k neighbors at varying distances.

We now demonstrate our approach with a manual walk-through. A manual walk-through is feasible because the basic process of kNN is intuitive and its outcome is easy to explain. To demonstrate our approach, we predict policy decisions for the following new scenarios for Bob: {Home} and {Home, Document}, using Bob’s initial policy specification shown in Table 1.

Consider the first new scenario, {Home}. Just by looking at Bob’s specification in Table 1, the reader may identify example 1 (i.e., {Home, Photo}) as closest to the new scenario, since it is the only example that includes the tag Home. As a result, we predict the policy decision for the new scenario {Home} as deny, i.e., as the decision of its nearest neighbor {Home, Photo}. This decision mirrors Bob’s assumption of data created at home being personal, and not exportable to the enterprise cloud. PyBE’s distance metric described in Section 5 uses a similar property for computing distance between two examples, and comes to the same conclusion.

Now consider the second new scenario, {Home, Document}. This time, there are two examples that seem to be equally close to the new scenario, i.e., {Home, Photo} and {Document}, since they each
have one tag in common with \{Home, Document\}. Since both the nearest examples have different policy decisions, our simple metric is insufficient. This is one of the motivations for introducing weights. Suppose Bob considers personal data created at home (i.e., the tag Home) to be most confidential. Therefore, Bob assigns Home more “importance” (i.e., a higher weight) than any other tag in terms of its influence on the policy decision. As a result, the new scenario \{Home, Document\} can be deemed closer to \{Home, Photo\} than \{Document\}, as Home has a higher weight and more say in the decision than the other tags, e.g., Document. Thus, export is denied for \{Home, Document\}, which aligns with Bob’s preference of data created at home being personal, and not exportable to the enterprise cloud.

The purpose of weights is not limited to breaking ties. Suppose Bob specifies another example, i.e., \{Document, Receipt\}, with decision allow. Now consider another new scenario \{Document, Receipt, Home\}. Without any knowledge of weights, it is easy to see that \{Document, Receipt\} would be the example closest to the new scenario \{Document, Receipt, Home\}, resulting in allow being predicted (i.e., there is no tie). At the same time, we know that Bob has allocated a higher weight to Home, since Bob considers home data to be confidential and important with respect to the WorkCloud target. The weights ensure that \{Document, Receipt, Home\} is closer to \{Home, Photo\} instead of \{Document, Receipt\}, and export is denied as per Bob’s actual security preference. Simply stated, weights enable the user to make some information tags beat others in the distance calculation. Our weighted metric described in Section 5.2 follows a similar rationale.

An important contribution of PyBE is that it recognizes that policy specification by users can be error-prone. PyBE uses active learning to engage the user in finding and correcting potential errors in their policy decisions. Our approach is inspired by the work of Gulwani [14], which detects noise in the user’s input-output examples, and recommends changes to incorrect outputs. Similarly, PyBE looks for noise in the user’s examples, which may indicate one or more incorrect policy decisions. We use our variant of kNN for this purpose. Note

Table 2: Bob’s extended set of examples for the WorkCloud policy target, with newly added examples in bold.

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario</th>
<th>Policy Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{Home, Photo}</td>
<td>deny</td>
</tr>
<tr>
<td>2</td>
<td>{Work, Photo}</td>
<td>allow</td>
</tr>
<tr>
<td>3</td>
<td>{Document}</td>
<td>allow</td>
</tr>
<tr>
<td>4</td>
<td>{Home, Document}</td>
<td>deny</td>
</tr>
<tr>
<td>5</td>
<td>{Home, Memo}</td>
<td>allow</td>
</tr>
</tbody>
</table>

Figure 2: \{Home, Memo\} disagrees with the majority policy decision of its nearest neighbors.

Figure 3: There is no majority policy decision among the nearest neighbors of \{Home, Photo\}.

that the objective of this task is to engage the user in finding errors in existing examples, and not to predict policy decisions for new examples. We explain our approach with the following extension to Bob’s policy:

Suppose Bob adds two additional examples, i.e., \{Home, Document\} with decision deny, and \{Home, Memo\} with decision allow. We borrow the first example (\{Home, Document\}) from the previous discussion on weights. The second example shows Bob’s policy for a memo created at home. Further, recall that Home has a higher weight, hence examples containing Home will be closer to each other than other examples not containing Home. Bob’s complete set of examples is shown in Table 2.

We perform a nearest neighbor search for the example \{Home, Memo\}, and identify \{Home, Photo\} and \{Home, Document\} as its nearest neighbors. An intuitive way of visualizing this group of examples is in the form of a graph, such that (1) the examples are vertices, and (2) directed edges are drawn from the example for whom the search was performed to its nearest neighbors. Figure 2 shows the graph for \{Home, Memo\}.

If we focus on the policy decisions of the vertices in Figure 2, we see that Bob’s decision for \{Home, Memo\} (i.e., allow) disagrees with the decision for both its nearest neighbors. This inconsistency or noise indicates one of two possibilities: (a) Bob made a mistake in labeling \{Home, Memo\} with the decision allow, or (b) Bob wanted to make a genuine exception for memos. Instead of making a guess, PyBE asks Bob. That is, we recommend Bob to label \{Home, Memo\} as deny for resolving this inconsistency. Bob may accept our recommendation, or reject it and make an exception. Using such interactive recommendations, PyBE engages Bob in correcting potential errors.

Figure 3 shows the nearest neighbor graph for \{Home, Photo\}, and illustrates another type of inconsistency. In this case, there is no majority consensus among the neighbors of \{Home, Photo\}. A similar
situation exists in the graph for \{Home, Document\}, which we do not show due to space constraints. If we look at the two graphs in Figure 2 and Figure 3, we realize that changing the policy decision of \{Home, Memo\} removes both the inconsistencies. Thus, PyBE capitalizes on the possibility that a few examples may cause the most noise, and recommends the user to change their labels. In our algorithm described in Section 5.3, we describe graph invariants to identify noise, and a greedy algorithm to find the optimal change. Section 7 demonstrates that our interactive approach finds five times as many errors as manual reviews by users.

Note that we do not claim to detect all errors, as the users’ examples may be completely consistent, but may still have errors. Instead, we recommend a best effort approach for engaging the user in detecting potential errors.

5 The PyBE Algorithm

This section describes our algorithm for predicting policy decisions, and the active learning approach. As stated previously, distance between policy examples is the distance between their scenarios, and policy decisions are the labels for the scenarios.

Our policy scenarios are Boolean functions over \(n\) variables (i.e., tags), denoted by \(\mathcal{P}_n\). However, we restrict our attention to functions that are conjunctions of variables (e.g., \(x_1 \land x_3 \land x_5\)). Such a function \(f\) can be represented as a set \(I(f) \subseteq \{1, 2, \cdots, n\}\) (e.g., if \(f = x_1 \land x_3 \land x_5\), then \(I(f) = \{1, 3, 5\}\)). Our policy scenarios belong to this restricted class (denoted by \(\mathcal{P}_n\)).

We had two requirements for the learning-algorithm to infer policy decisions: (I): non-parametric (does not rely on models with a fixed set of parameters). (II): easy explanation (easy to present to the user how the policy was inferred). For this reason we chose a variant of the \(k\) nearest neighbor (kNN) classifier [31]. A kNN algorithm simply “looks at” the \(k\) points in the training set that are nearest to the test input \(x\), counts how many members of each class are in the set, and returns that empirical fraction as the estimate.

Recall that our goal is to label a policy scenario \(p \in \mathcal{P}_n\) with the decision 1 (i.e., allow) or 0 (i.e., deny). We are also given a set of policy scenarios along with known labels (i.e., policy decisions). Our algorithm is inspired by the kNN algorithm and works as follows: given a new policy scenario \(p \in \mathcal{P}_n\), with an unknown label, we find the set of \(k\) policy scenarios \(N(p) = \{p_1, \cdots, p_k\}\) closest to \(p\) according to the metric \(\mu\) (described in the next subsection) and then associate the label to \(p\) that corresponds to the majority labels of the policy scenarios in \(N(p)\). Our variant of kNN only considers scenarios at the closest distance for inclusion in \(N(p)\). We describe how to address situations with no majority in Section 5.4.

We use active learning to assist the user in correcting potential labeling errors in the user’s policy examples. When we find that certain conditions are not true (e.g., the label of a policy scenario \(q \in \mathcal{P}_n\) is different from the majority label among its neighbors \(N(q)\)), we recommend a change in the label (e.g., change allow to deny). We now describe our metric \(\mu\), its weighted form \(\mu_w\), and the active learning phase. We design a new metric as integrating weights into existing metrics (e.g., jaccard distance) may incur significant re-engineering.

5.1 The Metric

Let \(f\) and \(g\) be two Boolean functions over \(n\) variables \(x_1, x_2, \cdots, x_n\). A metric between \(f\) and \(g\) (denoted by \(\mu(f, g)\)) can be defined as follows:

\[
1 - \frac{\#(f \oplus g)}{2^n}
\]

Where \(\oplus\) represents exclusive-or and \(\#(h)\) is the number of satisfying assignments of the Boolean function \(h\). Recall that computing the number of satisfying assignments of a Boolean function is a hard problem (\(\#\-P\) complete [31]). However, for our special case where scenarios are conjunctions of variables, this metric is easy to compute. Next, we describe the metric for the functions in the set \(\mathcal{P}_n\).

Consider two functions \(f_1\) and \(f_2\). Let \([n] = \{1, 2, \cdots, n\}\). Consider three sets of indices \(I_1, I_2\) (variables neither in \(f_1\) nor \(f_2\)), \(I_1^f\) (variables in \(f_1\) but not in \(f_2\)) and \(I_2^f\) (variables in \(f_2\) but not in \(f_1\)); i.e., \(I_{1,2} = [n] \setminus (I_1(f_1) \cup I_2(f_2))\), \(I_1^f = I_1(f_1) \setminus I_2(f_2)\), and \(I_2^f = I_2(f_2) \setminus I_1(f_1)\). An assignment \(\sigma\) is a Boolean vector of size \(n\) of the form \(\langle b_1, b_2, \cdots, b_n\rangle\) and \(f(\sigma)\) denotes the value of the function \(f\) for assignment \(\sigma\).

Consider an assignment \(\sigma = \langle b_1, b_2, \cdots, b_n\rangle\) such that \(f_1(\sigma) = 1\) and \(f_2(\sigma) = 0\). Then for all \(i \in I_1(f_1)\), \(b_i = 1\), and there should be at least one \(i \in I_2^f\) such that \(b_i = 0\). For \(i \in I_{1,2}\), \(b_i\) can assume any value. Consider all the indices in \(I_2^f\). There should be at least one \(j \in I_2^f\), such that \(b_j = 0\) (we want \(f_2(\sigma) = 0\)). Therefore, the number of satisfying assignments \(\sigma\), such that \(f_1(\sigma) = 1\) and \(f_2(\sigma) = 0\) is

\[
2^{k_1} (2^{k_2} - 1)
\]

where \(k_{1,2} = |I_{1,2}|\) and \(k_2 = |I_2^f|\). Explanation for the formula is as follows: all variables with indices in the set \(I_{1,2}\) can be given any value (resulting in the term \(2^{k_{1,2}}\)). All the variables with indices in \(I_2^f\) can be given any values as long as one of them is 0, so an assignment where all variables with indices in \(I_2^f\) is assigned 1 is excluded (this results in the term \(2^{k_2} - 1\)).

A symmetric argument shows that the number of satisfying assignments \(\sigma\) such that \(f_1(\sigma) = 0\) and \(f_2(\sigma) = 1\) is

\[
2^{k_1} (2^{k_1} - 1)
\]

where \(k_{1,2} = |I_{1,2}|\) and \(k_1 = |I_1^f|\). Adding the two terms, we have that \#\((f_1 \oplus f_2)\) is \(2^{k_1} (2^{k_1} + 2^{k_2} - 2)\). Therefore,
the metric $\mu(f_1, f_2)$ in this case is:

$$1 - \frac{2k_1 z(2k_1 + 2k_2 - 2)}{2^n}$$

where $k_{1,2} = |I_{1,2}|$, $k_1 = |I_1|$, and $k_2 = |I_2|$. Intuitively, $k_1$ is the number of variables that appear in $f_1$ but not in $f_2$, $k_2$ is the number of variables that appear in $f_2$ but not in $f_1$, and $k_{1,2}$ is the number of variables that appear in neither $f_1$ or $f_2$. Let $k = n - k_{1,2}$, which is the number of variables that appear in $f_1$ and $f_2$ (i.e., $k = |I(f_1) \cup I(f_2)|$). The metric $\mu(f_1, f_2)$ can be simplified as follows:

$$\mu(f_1, f_2) = 1 - \frac{2k_1 + 2k_2 - 2}{2^n}$$

Note that higher values of $\mu$ indicate closeness.

### 5.2 The Weighted Metric

For security policies, some variables are more important than others; e.g., recall the `Home` tag from Bob’s policy in Section 4.2. To incorporate the importance of variables we introduce a weighted version of our metric. As before, we will consider a Boolean function over $n$ variables $x_1, x_2, \ldots, x_n$. However, in this case we have two weights $w^0_i$ and $w^1_i$ associated with each index $1 \leq i \leq n$. The weight associated with an assignment $\sigma = \langle b_1, \ldots, b_n \rangle$ (denoted as $w(\sigma)$) is

$$\sum_{i=1}^{n} w^0_i (1 - b_i) + w^1_i b_i.$$ 

Given a set of Boolean assignments $S$, define $w(S)$ as $\sum_{\sigma \in S} w(\sigma)$ – the sum of weights of all assignments in $S$. Given a Boolean function $f$, $w(f)$ is the weight of the set of satisfying assignments of $f$. Using a simple recursive argument, the weight of all $2^n$ assignments $\{0, 1\}^n$ is:

$$\prod_{i=1}^{n} \left( w^0_i + w^1_i \right)$$

Given $n$ pair of weights $(w^0_i, w^1_i), \ldots, (w^0_n, w^1_n)$, a weighted metric between two Boolean functions $f$ and $g$ (denoted as $\mu_w(f, g)$) is defined as follows:

$$1 - \frac{w(f \oplus g)}{\prod_{i=1}^{n} (w^0_i + w^1_i)}$$

Note that if for all $i$ we have $w^0_i = w^1_i = 1$, we get the previous metric (i.e., the unweighted case).

As before, consider two Boolean functions $f_1$ and $f_2$ with index sets $I(f_1)$ and $I(f_2)$. Let the index sets $I^2_1$ and $I^2_2$ be as defined before. Define the following three quantities:

$$z_1 = \prod_{i \in I^2_1} (w^0_i + w^1_i) - \prod_{i \in I^2_2} w^0_i$$

$$z_2 = \prod_{i \in I^2_1} (w^0_i + w^1_i) - \prod_{i \in I^2_2} w^0_i$$

$$z = \prod_{i \in I(f_1) \cup I(f_2)} (w^0_i + w^1_i)$$

The metric $\mu_w(f_1, f_2)$ can be defined as:

$$\mu_w(f_1, f_2) = 1 - \frac{z_1 + z_2}{z}$$

The argument is exactly same as before. The reader can check that for the unweighted case (i.e., for all $i$ we have $w^0_i = w^1_i = 1$) we get the previous metric back.

**Setting weights:** Next we describe an algorithm to set weights. Given a set of variables $V = \{x_1, \ldots, x_n\}$, suppose we are given a partial order $\leq$ on $V$ (e.g., $x_i \leq x_j$ means that $x_j$ is more “important” than $x_i$). Next we construct a function $L: V \rightarrow [n]$ that assigns integers between 1 and $n$ to each variable in $V$ and has the property that $x_i \leq x_j$ and $j \neq i$ implies that $L(x_i) > L(x_j)$.

We can assign higher weights $w^1_i$ to variables that have a lower value according to the function $L$ and set all the weights $w^0_i$ to 1. Note that it is not necessary to precisely define a mechanism for assigning weights, as long as the ordering imposed by $L$ is preserved.

### 5.3 Active Learning

Ideally, users would provide accurate examples to PyBE. However, as even expert users are not always accurate [18, 55], we expect a small margin of error in the policy decisions provided by the user; e.g., a typo resulting in 1 being accidentally marked as 0. We use active learning to find and correct potentially incorrect policy decisions, by asking users to relabel certain chosen scenarios. Relabeling samples to remove errors has been shown to be effective even with non-experts by prior work [43].

In our approach, the scenarios and their nearest neighbors are arranged as a graph, which allows us to relabel existing scenarios in a systematic manner if certain invariants on the graph are not true. In other words, the graph we are about to describe gives us a systematic way to evaluate the conditions that may indicate user error.

Let $G = (V, E, L_v, L_E)$ be a 4-tuple where $V \subseteq \mathcal{P}_n$ is the set of labeled policy scenarios, $E \subseteq V \times V$ is the set of edges, $L_v$ maps each vertex $v \in V$ with a label 1 (signifying allow) and 0 (signifying deny), and $L_E$ labels each edge $e \in E$ with a non-negative real value (i.e., $L_E(v, v')$ is $\mu(v, v')$, which is the distance between the scenarios $v$ and $v'$). The set of neighbors $N(v)$ of a vertex $v \in V$ is the set $\{v' | (v, v') \in E\}$ and intuitively represents all the nearest-neighbors of the policy scenario $v$.

**In-v-1:** Major label exists. This invariant states that for all $v \in V$, its set of neighbors $N(v)$ have a majority label (i.e., more than $\frac{|N(v)|}{2}$ vertices in $N(v)$ have the same label $L_v(v)$).

**In-v-2:** Agreement with the majority label. This invariant states that if invariant Inv-1 is true, then for every

---

1 Such a function can be constructed by topologically sorting a directed graph whose nodes are $V$ and there is an edge from $x_j$ to $x_i$ ($j \neq i$) iff $x_j \leq x_i$. 
v ∈ V its label \( L_V(v) \) agrees with the majority label of its neighbors \( N(v) \).

**Intuitively we want the graph \( G \) corresponding to our policies to satisfy invariants Inv-1 and Inv-2. If the graph \( G \) violates either of the invariants, then we recommend relabeling of the policy scenarios to the user.**

Figure 4 shows instances of the graph for some vertex \( p \) that violate the invariants. In Figure 4a, there is no majority label among \( p \)'s neighbors, which can be resolved by relabeling either \( q \) or \( r \). Further, in Figure 4b, the label on \( p \) disagrees with the majority, which can be resolved by relabeling \( p \).

We use a simple greedy approach to recommend changes: Consider a function \( Ψ(G) \) that counts the total violations of both Inv-1 and Inv-2 in graph \( G \). Further, consider a function \( Φ(v,G) \) that measures the impact of a potential label change on violations, i.e., returns the decrease in \( Ψ(G) \) after a temporary change in the label of \( v \) (i.e., \( L_V(v) \)). The label change that causes the maximum decrease in \( Ψ(G) \) is optimal. Therefore, at each iteration, we find the optimal vertex, \( v_{\text{opt}} \), by maximizing \( Φ(v,G) \) over all \( v ∈ V \setminus V_{\text{visited}} \), where \( V_{\text{visited}} \) is the set of all vertices that have been recommended to the user previously. We add \( v_{\text{opt}} \) to \( V_{\text{visited}} \), and recommend the user to change \( L_V(v_{\text{opt}}) \). If the user accepts, we change \( L_V(v_{\text{opt}}) \). We reiterate until all the vertices are visited or until there are no more violations.

**5.4 Prediction with No Majority**

As described previously, we predict the label (i.e., policy decision) for a new policy scenario \( p \) as the majority label of its nearest neighbors \( N(p) \). If there is no majority label, we use the following method for prediction:

We eliminate the first neighbor that is not a mutual neighbor, i.e., if there is a labeled policy scenario \( q \) such that \( q ∈ N(p) \) but \( p \notin N(q) \), we remove \( q \) from \( N(p) \), thereby converging on a majority. In case such elimination is not possible, i.e., if all neighbors in \( N(p) \) are mutual neighbors, we deny by default. Our method considers the value of the distance between neighbors to resolve a tie, instead of randomly discarding one scenario (i.e., by considering only an odd number of scenarios in \( N(p) \)). In Section 7, we demonstrate that PyBE performs better than a baseline of random guessing, and that such cases were rare, i.e., less than 6% test scenarios had no majority, and less than 3% were denied by default.

**6 Evaluation**

We performed an IRB-approved feasibility study with expert users to evaluate the effectiveness of our approach. We chose experts under the hypothesis that they prefer more complex policies, the complexity of which makes them challenging to predict. Support for this hypothesis comes from the fact that non-expert users are more likely to employ binary security practices, (e.g., only visiting known sites rather than deciding based on security-related attributes like usage of https [18]) and evidence that knowledge of security risks can increase sensitivity to security when making data decisions [36]. Note that no personally identifiable information (PII) was collected from the participants.

We plan to release our tool and source code after publication, to allow a broader audience to use PyBE. A sanitized version of our dataset will also be released.

The following research questions motivate our study:

**RQ1** How accurate are our predictions for random, unlabeled scenarios that may occur at runtime?

**RQ2** What are the causes for incorrect predictions?

**RQ3** Do users make mistakes in their examples?

**RQ4** Does our active learning approach help the user find mistakes in their examples?

This section describes the study setup, the data collection and experiments. Section 7 describes the results. Due to space constraints, this section describes the core methodology of the feasibility study; the literal scripts used during the study can be found in Appendix B.

**6.1 Study Setup**

In this study, participants were asked to consider a smartphone environment, where personal and work data would be at risk of unauthorized exfiltration from the device. We now describe the participants (i.e., expert users), policy targets and information tags involved in the study.

**Expert Users:** We recruited 8 graduate student researchers from a security research lab for this study (denoted as P1→P8). Our participants had at least 1 academic year of experience (2.5 years on average) in security research at the time of this study, including at least one research project and two graduate-level courses in security or privacy. We use the security-focused coursework and research as an indicator of general security-awareness, and assume the participants to be well-aware of their own security and privacy requirements. Additionally, we confirmed that all our participants used their smartphones for both work and personal data. Finally, through an informal discussion of participant background knowledge, we confirmed that the participants...
were aware of the threat of exfiltration of work and personal data by third party applications on smartphones, as discussed by prior work (e.g., TaintDroid [11]).

**Policy Targets:** Table 3 provides the policy targets (i.e., policies) used in our study. The targets are similar to the *WorkCloud* target discussed in Section 4, and either (a) restrict the destination Web domain to which data can be exported (i.e., *WorkCloud* and *PersonalCloud*) or (b) restrict the exporters (i.e., applications) that are permitted to export data: i.e., *WorkEmailApp*, *PersonalEmailApp* and *SocialApp* regulate export by the user’s work email client, personal email client, and social network client (e.g., the Facebook app) respectively. As described previously, each target is treated as an independent policy.

**Information Tags:** We provided users with 9 pre-defined secrecy tags, based on tags available in popular note-taking applications (e.g., Google Keep, Evernote). To enable our experts to create any complex policy they desired, we allowed them to create new tags as well. The tags (user-created or predefined) were primarily of two kinds, namely tags that defined the location or time at which the information was created (e.g., *Work*, *Afterhours*) or the type or class of information (e.g., *Receipt*, *WhiteboardSnapshot*). The tags used in this study are provided in Appendix A.

### 6.2 Data Collection

This section describes the approach used for collecting the policy examples and weights from participants.

**1. Collecting Policy Examples:** Participants were provided with our predefined tags, but were also allowed to create their own tags. Participants were instructed that they could combine tags into complex scenarios for creating examples. We placed no constraint on the number of example scenarios each participant could provide. For each scenario, participants were required to label policy decisions for the 5 targets described previously in Table 3. Note that we collected labels for two more targets, but discarded them before testing to reduce user fatigue.

A preliminary analysis of the examples collected from our participants led to two interesting observations: (1) Our participants created a total of 31 unique tags, out of which about 58% (or 23) were specific to individual participants, while only 7 tags were commonly used by all in their examples, and (2) Out of the 246 example scenarios collected across participants, over 76% were specific to individual participants, and only 7 were common among all 8 participants. These observations indicate that relevant data-use scenarios may be unique to the individual, even among student researchers from the same research lab, further motivating our research into generating user-specific policies for user-specific data.

**2. Obtaining Weights:** On average, each participant used about 14 unique tags in their examples. As ordering a large number of tags can be tiring, we categorized tags into semantic groups. The participants were provided with this semantic grouping, and were first (1) allowed to customize group memberships of tags as per their understanding, and then (2) instructed to provide a partial order over the groups in a spreadsheet. Participants were provided with a basic partial order generated by the authors, and could start from scratch, or customize the provided ordering. We confirmed each partial order relation by reading it out to the user; e.g., by asking if “j is more important than i” to confirm i ; j. We then transformed the orders to weights using the approach described in Section 5.2. For additional illustration, Appendix B.2 provides P1’s tag groups (Figure 6) partial order on the groups (Figure 7).

Finally, participants were informed that they could provide different partial orders for different policies, but most participants chose to keep a single general order. We describe the impact of this decision in Section 8.

### 6.3 Experiments

This section describes the experiments for identifying user errors and testing prediction for random scenarios.

**1. Identifying Errors:** The review of examples was carried out 3 months after the initial specification, as most participants were unavailable over the summer break. We performed a two-step experiment to help participants identify and correct errors in their policy decisions.

First, participants performed a manual review of their initial specification. Participants were provided with a spreadsheet containing their policy examples (one sheet per policy target), and could change any policy decision they desired. For each update, participants were instructed to indicate a cause to justify the change (e.g., correcting an error, change of mind, inability to decide). Finally, participants provided a justification for each change (e.g., “Work is confidential”), providing the helpful context for analyzing the results (Section 8).

After the manual review, we performed a PyBE-assisted review using the approach described in Section 5.3. We treat each participant-policy combination as a separate policy specification problem; hence, a separate review was performed for each such case (i.e., 8 users and 5 policies make 40 total cases). As we used

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**Table 3: Policy targets and the actions they control.**

<table>
<thead>
<tr>
<th>Policy Target</th>
<th>Action Controlled</th>
</tr>
</thead>
<tbody>
<tr>
<td>WorkCloud</td>
<td>Export of data to the enterprise cloud</td>
</tr>
<tr>
<td>PersonalCloud</td>
<td>Export of data to the personal cloud</td>
</tr>
<tr>
<td>WorkEmailApp</td>
<td>Export of data by the enterprise email app</td>
</tr>
<tr>
<td>PersonalEmailApp</td>
<td>Export of data by the personal email app</td>
</tr>
<tr>
<td>SocialApp</td>
<td>Export of data by the social network app</td>
</tr>
</tbody>
</table>

**Listing 1:** A suggestion made by the PyBE algorithm during the interactive review process.

**Suggestion:** For {Note}, WorkCloud = DENY. Agree?(y/n)
the changed examples from the manual review; any errors discovered using this approach were additional. Our algorithm presented the participant with a series of suggestions (i.e., examples with corrected policy decisions, as shown in Listing 1). If the participant accepted the suggestion, we confirmed with the participant that the original decision was in error, and recorded it as an error found by PyBE. If the participant rejected, we asked for a short justification to understand the participant's policy preferences. We stopped at 15 suggestions for each participant-policy case to limit fatigue.

2. Testing with Random Scenarios: For each participant, we randomly generated $n/2$ new policy scenarios, where $n$ was the number of scenarios initially provided by the participant. The random scenarios were created with the tags used in the participant’s initial examples. The intuition is that the tags provided by the participant are relevant to the participant; hence scenarios composed of them must be relevant as well. To mitigate labeling fatigue, the random scenarios included at most 3 tags.

Participants provided the ground truth policy decisions for their test scenarios, for each of the five policy targets. Apart from indicating “Allow” or “Deny”, participants were also provided the “I don’t know”, in which case we substituted the scenario with another random test scenario. We predicted the policy decision for each test scenario using our algorithm. We then asked participants to confirm their decisions for incorrect predictions, provide short justifications, and conducted short, informal interviews that helped us gain insight into the decisions.

7 Results

This section describes the results of our experiments, i.e., PyBE’s accuracy in predicting policy decisions for new scenarios, and its effectiveness in assisting participants in finding incorrect policy decisions in their examples. We start by briefly describing the datasets collected during the initial policy specification and testing; a detailed split across participants can be found in Appendix C.

Specification dataset: The 8 participants provided 246 example scenarios in total, with policy decisions for 5 policy targets, resulting in a total of 1,230 initial labeled policy examples.

Testing dataset: We generated a total of 122 random test scenarios across 8 participants, which when labeled with ground-truth policy decisions by participants for 5 policies, resulted in 610 test examples.

7.1 Accuracy of Predictions

Our algorithm predicted decisions for all of the participants’ test scenarios.\(^2\) The actual prediction time was negligible (i.e., less than 1 second for all the examples per participant). Further, for less than 6% (36 out of 610) of our test examples we had no majority label (i.e., a tie). Applying the tiebreaker discussed in Section 5.4 resolved 19 of these ties, while the rest (i.e., 3% or 17 out of 610) were denied by default. We now discuss the accuracy of PyBE’s predictions.

On comparing our predicted decisions with ground-truth decisions provided by participants, we observe that PyBE predicts policy decisions with an average accuracy of over 76% across all participants (RQ1). When analyzing the accuracy, it is important to note that each participant-policy combination is treated as an independent policy specification problem, and hence forms a separate test case. We first define a baseline and naive approach against which we evaluate PyBE’s accuracy.

1. The CoinFlip baseline: The CoinFlip baseline provides the measure of accuracy of random guessing, with an equal probability of a 0/1 outcome on each flip.

2. The MostFreq naive approach: We define MostFreq as an approach that predicts the most frequent or majority policy decision from the specification dataset, independently for each participant-policy problem. For example, if P1 generally allows export to WorkCloud, MostFreq will predict allow for all new test examples for that the P1-WorkCloud policy specification problem. The insight behind MostFreq is that a naive learner is likely to pick the majority class to benefit from the consistent trend in the participant’s policy decisions.

Table 4 shows the comparison of PyBE’s accuracy with CoinFlip, for each of the 40 participant-policy cases. PyBE not only performs better in terms of average accuracy (i.e., 76>50), but also for most (i.e., all but 3, or 92%) of the participant-policy problems.

Table 5 shows a comparison between the performance of PyBE and the naive approach MostFreq. PyBE not only performs better than MostFreq in terms of average accuracy (i.e., 76>71), but also in 29 out of 40 (i.e., 72.5%) participant-policy cases, and for 75% of the participants. Note that although MostFreq’s average accuracy can be said to be close to PyBE, it has high variance, with accuracy dropping to 17% in some cases. This is because of MostFreq’s over-dependence on the probability distribution of the training samples, a flaw PyBE is not susceptible to. We discuss the causes of incorrect predictions (RQ2) in Section 8.

7.2 Effectiveness of Active Learning

Table 6 shows the number of labeling errors found by the participant through the manual review, followed by the additional errors found using PyBE’s interactive approach. Errors found by PyBE’s approach are additional as we use the corrected dataset from the manual review for the PyBE-assisted review, as described in Section 6.3.

Out of 1,230 total examples in the specification
Table 4: Accuracy of PyBE in comparison with the CoinFlip (abbreviated to CF) baseline, for all 40 user-policy cases. Cases where the accuracy of CF is greater are highlighted in bold.

<table>
<thead>
<tr>
<th>Policy Target</th>
<th>P1 CF</th>
<th>P2 CF</th>
<th>P3 CF</th>
<th>P4 CF</th>
<th>P5 CF</th>
<th>P6 CF</th>
<th>P7 CF</th>
<th>P8 CF</th>
</tr>
</thead>
<tbody>
<tr>
<td>WorkCloud</td>
<td>0.96</td>
<td>0.50</td>
<td>0.73</td>
<td>0.48</td>
<td>0.66</td>
<td>0.49</td>
<td>0.83</td>
<td>0.49</td>
</tr>
<tr>
<td>PersonalCloud</td>
<td>0.77</td>
<td>0.50</td>
<td>0.55</td>
<td>0.5</td>
<td>1.00</td>
<td>0.50</td>
<td>0.75</td>
<td>0.52</td>
</tr>
<tr>
<td>WorkEmailApp</td>
<td>0.96</td>
<td>0.50</td>
<td>0.55</td>
<td>0.51</td>
<td>0.83</td>
<td>0.47</td>
<td>0.83</td>
<td>0.47</td>
</tr>
<tr>
<td>PersonalEmailApp</td>
<td>0.77</td>
<td>0.51</td>
<td>0.55</td>
<td>0.49</td>
<td>1.00</td>
<td>0.50</td>
<td>0.75</td>
<td>0.48</td>
</tr>
<tr>
<td>SocialApp</td>
<td>0.81</td>
<td>0.51</td>
<td>0.73</td>
<td>0.49</td>
<td>0.75</td>
<td>0.52</td>
<td>0.92</td>
<td>0.49</td>
</tr>
<tr>
<td>Average</td>
<td>0.85</td>
<td>0.50</td>
<td>0.62</td>
<td>0.49</td>
<td>0.85</td>
<td>0.50</td>
<td>0.82</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Table 5: Accuracy of PyBE in comparison with the MostFreq (abbreviated to MF) approach, for all 40 user-policy cases. Cases where the accuracy of MF is greater are highlighted in bold.

<table>
<thead>
<tr>
<th>Policy Target</th>
<th>P1 MF</th>
<th>P2 MF</th>
<th>P3 MF</th>
<th>P4 MF</th>
<th>P5 MF</th>
<th>P6 MF</th>
<th>P7 MF</th>
<th>P8 MF</th>
</tr>
</thead>
<tbody>
<tr>
<td>WorkCloud</td>
<td>0.96</td>
<td>0.85</td>
<td>0.73</td>
<td>0.63</td>
<td>0.66</td>
<td>0.17</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
<td>PersonalCloud</td>
<td>0.77</td>
<td>0.69</td>
<td>0.55</td>
<td>0.91</td>
<td>1.00</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>WorkEmailApp</td>
<td>0.96</td>
<td>0.85</td>
<td>0.55</td>
<td>0.64</td>
<td>0.83</td>
<td>0.17</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
<td>PersonalEmailApp</td>
<td>0.77</td>
<td>0.69</td>
<td>0.55</td>
<td>0.91</td>
<td>1.00</td>
<td>1.00</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>SocialApp</td>
<td>0.81</td>
<td>0.73</td>
<td>0.73</td>
<td>0.46</td>
<td>0.75</td>
<td>0.92</td>
<td>0.92</td>
<td>0.58</td>
</tr>
<tr>
<td>Average</td>
<td>0.85</td>
<td>0.76</td>
<td>0.62</td>
<td>0.71</td>
<td>0.85</td>
<td>0.65</td>
<td>0.82</td>
<td>0.72</td>
</tr>
</tbody>
</table>

*The CoinFlip baseline values shown are the mean of 50 executions with a 95% confidence interval less than 0.03.

We manually analyzed each of the 141 incorrectly predicted test examples, using the following information collected during our study: (1) the justifications provided by the participants for their decisions, (2) the nearest neighbors of the test example, (3) the weights of the tags involved, and (4) all examples from the specification dataset that contain tags in common with the test example. The rest of this section describes the four causes of incorrect predictions that we identified. A detailed breakdown of the causes across participants and policies is provided in Table 10 in Appendix D.

1. **Misconfigured Weights**: We found that a majority of our incorrect predictions (79 out of 141, or over 56%) were caused because the weights set by the participants contradicted their actual security preferences. We confirmed our findings using justifications from participants that clearly indicated the tag or security preference that influenced their policy decision for a test example.

   For instance, consider an incorrect prediction for P1’s PersonalCloud policy, where PyBE predicted the policy decision allow for the test example {WhiteboardSnapshot, Work, ScannedDocument}. The user provided the ground-truth decision of deny, and justified with the quote “no work data to personal cloud”. That is, the tag Work was confidential and hence important to P1 with respect to the PersonalCloud policy target. This preference of Work being important is also consistent for all but one of P1’s examples containing Work, as shown in Table 7. However, this importance was not reflected in the weights, i.e., P1 mistakenly assigned Work data a lower weight (i.e., weight 2) by ordering it lower than personal data (i.e., weight 4). This resulted in the test example being matched with personal examples (e.g., {MedicalFacility, ScannedDocument}) that allowed export for PersonalCloud.

   On raising the weight of Work to 5 (i.e., above personal tags), the test example was correctly found closer to {Work, ScannedDocument}, resulting in a correct prediction of deny. Note that this increase in weight is not arbitrary, but guided by evidence of the user’s security preferences. On correcting all misconfigured weights, we manually confirmed that our overall accuracy rose to 89%. This includes most predictions for P2 and P5 for whom PyBE had the lowest accuracy.

   Since misconfigured weights caused the maximum incorrect predictions (79 out of 141, or 56%), we investigated further, and made two interesting observations:
School and Work to be different due to off-campus employment. However, before testing, P8 started working at the school, which resulted in similar decisions for School and Work. P8 admitted to this change during the post-testing interview. All cases in this category were similarly confirmed.

3. Unconfirmed Policy Change: For a small number of incorrect predictions (15 out of 141, or about 11%), we observed a clear contradiction between the participant’s examples during specification and testing, but could not get a confirmation from the participant. For example, for P8’s test example \{SavedToDevice, Audio\}, the ground truth label allows export for the WorkCloud policy, but all except one of P8’s initially specified examples containing SavedToDevice or Audio deny export to the WorkCloud. Without additional information, we classify such contradictions as unconfirmed policy changes.

4. Tag Confusion: The least number of errors (i.e., 12 out of 141, or about 8.5%) were caused due to the ambiguity of some tags. The location or time-based tags (e.g., Home and Afterhours) were intended to indicate the location or time of creation of data. However, as we did not place strict constraints, our participants also created scenarios where such tags could be used by themselves (e.g., the scenario \{Home\} could mean data created at home). Justifications indicated that while participants could comprehend the scenarios they had created, a few random test scenarios (in case of 3 participants) caused confusion. For example, \{Afterhours, Audio, Document\} could mean Audio created after hours, and added to a document whose origin is unknown, or a document created after hours, and added to an audio recording.

Finally, we exclude five incorrect predictions from P8’s test dataset from our categorization, i.e., 3 for PersonalEmailApp and 2 for WorkEmailApp, as the participant was unable to decide unless they knew the identity of the email receiver, which gave us no information. We did not face this situation with any other user or example.

9 Lessons

The lessons we learned from our feasibility study highlight aspects of correctly using PyBE in practice, and also motivate problems for future work.

Lesson 1: Weight assignment should reflect security, as
well as general privacy preferences. If policy targets are semantically related to the tags, a generic weight assignment for multiple targets may be inaccurate.

**Lesson 2:** Addressing “potential” change in the policy is imperative. The user may change some or all of their security policy goals without informing the system.

**Lesson 3:** The notion of importance depends on the security goals, as users may want to consider extremely non-confidential data as important (i.e., declassifiers). If the system’s goal is security, then the most confidential tag may have the highest weight; and for usability, the most non-confidential tag.

**Lesson 4:** Tag semantics should be carefully considered for applying PyBE. Users may be able to reason about examples they create, and may even desire the expressibility of multiple label semantics (i.e., “created at” or “derived data”); however, this expressibility may cause confusion when reasoning about random examples.

10 Future Directions

Our evaluation of PyBE demonstrates feasibility, and shows promise for further exploration in this area. We now discuss two future directions, namely (1) adapting PyBE for non-experts and (2) adapting to change.

Adapting PyBE for non-experts: Measuring the usability of PyBE with non-experts is a natural direction for future research. Additionally, we make the following recommendations for tasks that may be performed differently for non-experts.

1. Collecting examples: To ease the burden of creating tags, non-experts may be provided with a large and diverse collection of tags (e.g., the 40 tags obtained in our study) as a baseline for specifying examples. Further, usable interfaces may be considered for non-experts (e.g., “interactive drop downs” [20, 21] to collect examples).

2. Collecting Weights: Collecting weights from non-experts is another challenge for future work. Future work may consider using visual “sliders” for weight collection, for precise and usable weight assignments.

3. System Integration: PyBE may be integrated into existing systems that protect user-specific data from disclosure to the network (e.g., Weir [32] and Aquifer [33]). On such systems, users may want to override policy predictions by PyBE at runtime, or provide feedback, requiring a trusted path between the user and PyBE. A feedback mechanism may also improve future predictions.

Adapting to Change: Another direction for future work is detecting potential change in the user’s policy. While detecting change may be impossible without external input in some cases, there is value in evaluating solutions in other cases. Lessons from prior work that measures policy changes for file access control may be used to determine the causes for policy change [46]. Persuasive technologies designed by prior research may also provide ways to encourage the user to report change when it happens [7, 30, 35]. Future work may also be directed at predicting which example or tag is likely to change, using existing information (e.g., weights, frequency in examples). Our intuition is that strategies used for cache replacement (e.g., least recently used or LRU [42]) may apply, at least as a starting point.

Finally, active learning may also be used to suggest new examples to the user, which is not the focus of this paper, and lies in the broader scope for future work.

11 Threats to Validity

In this paper, we provide a general framework for specifying policies for user-specific data. Individual aspects of our framework may be iteratively refined in the future. We identify specific limitations of the current state of our approach and its evaluation as follows:

We evaluate feasibility with expert users. While our participants provide a significant number of policy examples, the number of participants is small, hence we cannot generalize to the broader user population. However, because this specialized set of users are likely to have more complex policies than most users, we view our feasibility study as a sufficient “stress test” of PyBE.

Additionally, since even expert users can make bad security decisions [55], our expert-specified policy examples are not expected to be error-free. Indeed, we use our interactive approach to help users find potential errors.

Our policy scenario is described as a conjunction of variables (Section 4.1). While it is easy to see how such a format may generalize to any policy that may be expressed as a conjunction of data objects or conditions, a thorough evaluation of expressibility may be required.

Finally, in Section 5.3, we propose a simple greedy approach to satisfy graph invariants. A more complex approach (e.g., using dynamic programming) may be integrated into PyBE without any significant changes.

12 Conclusion

We introduced the paradigm of Policy by Example (PyBE) for user-specific policy specification. PyBE enables users to express data-use scenarios in policy examples, and predicts policy decisions for new scenarios. In our feasibility study, PyBE demonstrated better prediction performance than naive approaches. A key contribution of PyBE is its active learning approach for engaging users in finding and potentially incorrect policy decisions in their examples, which we demonstrated to be five times as effective as manual reviews. Finally, we analyzed our incorrect predictions and learned lessons that motivate future research in this promising new domain.
References


Tags used in the User Study

Figure 5 shows the tags used in this study. We provided 9 tags, while the rest were created by users.

Feasibility Study details

The data collection and experiments were performed using semi-structured interviews. Most tasks (i.e., collecting examples, reviewing examples, and testing) took about 75 minutes, whereas collecting weights took about 20 minutes on average. While breaks were offered as a part of the experimental design, no participant elected to take their break.

B.1 Collecting Examples

- In this task, you will provide context-policy examples.
  - You will be given a list of predefined context tags. You can use 0 or more of these tags, and also create your own tags.
  - You may combine tags to describe the context of a scenario. You will then be required to indicate a policy decision (i.e., 0 for deny and one for allow) for the policies provided.
  - Each line on the example sheet has space for the context (i.e., combination of tags), and a column for each policy.
B.2 Collecting Weights

This phase consisted of two tasks, grouping tags and ordering groups. We provide the instructions given to users as follows:

B.2.1 Grouping tags

We provide an example of customized tag-group memberships in Figure 6.

- In this task, you will receive a spreadsheet containing groups, and information tags included in those groups. Note that the tags may include not only the tags you defined in the initial interview, but also tags defined by other users.

- We have grouped tags that seem to be dealing with data of similar secrecy value. For instance, all the work-related tags such as “Work”, “WorkTravel” are in the group “Work”.

- The task is to verify group memberships, such that every tag belongs to the correct group as per your understanding.

- You can move tags around, i.e., remove them from one group, and add to another, but you cannot add, remove, or rename the groups themselves.

- The spreadsheet will also include a comments column, if you want to make a comment about a specific group, although comments are not required.

- Finally, the spreadsheet will include descriptions for some group names for reference.

B.2.2 Ordering Groups

- In this task, you will be given a set of partial order relations among the groups described in the previous experiment. This set of relations is only a baseline.

- A relation between groups A and B, such that A:B, means that B is more important than A. Since our policies are information secrecy-related, more important may be understood as more sensitive.

- Your task is to modify (i.e., add or remove) the given list of relations, i.e., to customize the orders according to the your data secrecy/privacy preferences.

- You will also be allowed to use your initial group assignment for reference.

- It is possible that the ordering of groups may be different for different policies. Therefore, you will be able to use different sets of relations for different policies (total 7 policies). Please indicate if you want to use the same order for all policies, or if you would prefer to use different orders. This choice can be made or modified at any point of time throughout this task.
Figure 6: Screenshot of the tag groups customized by P1

<table>
<thead>
<tr>
<th>Group Name</th>
<th>Tags</th>
</tr>
</thead>
<tbody>
<tr>
<td>Work</td>
<td>Work, WorkTravel, ManagersHome, FromWorkEmail, BusinessCard, Code</td>
</tr>
<tr>
<td>Personal</td>
<td>Home, PersonalTravel, FromPersonalEmail, Afterhours, Weekends, Night, EarlyMorning, Traveling, School, GirlfriendsHome, Torrent, Contacts</td>
</tr>
<tr>
<td>Documents</td>
<td>ScannedDocument, WhiteboardSnapshot, Screenshot, SavedToDevice</td>
</tr>
<tr>
<td>Recordings</td>
<td>Audio, Video, Photos</td>
</tr>
<tr>
<td>Notes</td>
<td>Postit, Notes, Memo</td>
</tr>
<tr>
<td>Todo</td>
<td>CalendarLink, Reminder</td>
</tr>
<tr>
<td>Medical</td>
<td>MedicalFacility, HealthCenter</td>
</tr>
<tr>
<td>Finance</td>
<td>TaxOffice, LawyersOffice, Receipts</td>
</tr>
<tr>
<td>History</td>
<td>LocationData, BrowserHistory, History, Bookmarks, RecentlyDeleted</td>
</tr>
</tbody>
</table>

Figure 7: Screenshot of P1’s ordering of tag groups.

- In the end, I will confirm each order, for each policy (if the user chooses to have different orders for different policies). For instance, if the user enters A:B, I will confirm “is B more important than A?”.
- Finally, you have the option of continuing to the next experiment after a break of 5-10 minutes, or calling it a day.

B.3 Review of Examples

The review phase consisted of two tasks, namely a manual review, and a semi-automated review using active learning. This section provides the scripts for both tasks.

B.3.1 Manual Review

- In this task, you will receive a set of spreadsheets (one per policy) containing your examples (i.e., the context label + policy decision) for that policy.
- This is an opportunity for you to review your examples, and modify the policy decision if necessary. The context labels cannot be modified.
- For each change you make, you will then indicate the cause of the change in the respective column of one of the following hints:
  - “I have changed my mind”: i.e., my policy preferences have changed.
  - “It seems I made an error before”
  - “I don’t understand this policy example”: This could happen if you do not remember why you specified the policy, or are having trouble expressing it with tags you provided/used.
- Finally, for each change you make, please provide justification in the last column. This column may also be used for reasons other than the said hints.
- The investigator will go through the changes, and may ask you to provide any missing justifications or causes.

B.3.2 Semi-automatic Review

- In this task, our algorithm will suggest policy decisions for existing context labels that you have previously provided.
- You must either agree (y) or disagree (n) to the decision. You can also skip by entering n twice.
- For every decision that you disagree to, please provide a short justification.
  - For example, the algorithm may suggest Denial of export to the WorkCloud when the data object with the context created at Home, Photo. This suggestion will be presented as follows: Home+Photos, WorkCloud = DENY (y/n)?
  - If you agree, the algorithm will make another suggestion, or stop.
  - If you disagree, the algorithm will provide a text input for the justification.
- The task will consist of at most 15 questions.
Table 8: Number of unique example scenarios created by each user, as well as the total number of policy examples created after assigning decisions for 5 policies.

<table>
<thead>
<tr>
<th>Users</th>
<th>Example scenarios created (n)</th>
<th>Policy examples for 5 policies (n = 5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>52</td>
<td>260</td>
</tr>
<tr>
<td>P2</td>
<td>23</td>
<td>115</td>
</tr>
<tr>
<td>P3</td>
<td>25</td>
<td>125</td>
</tr>
<tr>
<td>P4</td>
<td>24</td>
<td>120</td>
</tr>
<tr>
<td>P5</td>
<td>33</td>
<td>165</td>
</tr>
<tr>
<td>P6</td>
<td>26</td>
<td>130</td>
</tr>
<tr>
<td>P7</td>
<td>21</td>
<td>105</td>
</tr>
<tr>
<td>P8</td>
<td>42</td>
<td>210</td>
</tr>
<tr>
<td>Total</td>
<td>246</td>
<td>1,230</td>
</tr>
</tbody>
</table>

B.4 Testing with Random Examples

In this section, we describe the script for the phase of testing with random examples. This phase was split into two tasks as well, i.e., the task of labeling samples, and of the post test review.

B.4.1 Labeling Test Samples

- In this task, you will receive a set of spreadsheets (one per policy) containing examples (i.e., the context).
- Your task is to label the policy decision (allow/-deny/I don't know) for each example.

B.4.2 Post-test Review

- In this task, our algorithm will ask you to confirm policy decisions that you have previously provided.
- Please agree (y) or disagree (n) with your decision.
- For every decision that you agree to, please provide a short justification.

C Datasets

The number of examples per participant in the specification and testing datasets are shown in Tables 8 and 9 respectively.

D Detailed split of causes of errors

A detailed split of the causes of error, across users and policies, can be seen in Table 10.

Table 9: Number of random policy scenarios created for testing predictions per participant. Participants provide policy decisions (and PyBE predicts) for 5 policies.

<table>
<thead>
<tr>
<th>Users</th>
<th>Random Test Scenarios (n)</th>
<th>Labeled Test examples for 5 policies (n = 5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>26</td>
<td>130</td>
</tr>
<tr>
<td>P2</td>
<td>11</td>
<td>55</td>
</tr>
<tr>
<td>P3</td>
<td>12</td>
<td>60</td>
</tr>
<tr>
<td>P4</td>
<td>12</td>
<td>60</td>
</tr>
<tr>
<td>P5</td>
<td>16</td>
<td>80</td>
</tr>
<tr>
<td>P6</td>
<td>14</td>
<td>70</td>
</tr>
<tr>
<td>P7</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>P8</td>
<td>21</td>
<td>105</td>
</tr>
<tr>
<td>Total</td>
<td>122</td>
<td>610</td>
</tr>
</tbody>
</table>
Table 10: Breakdown of incorrect predictions into misconfigured weights (W), policy change (C), unconfirmed policy change (U) and label confusion (L), across all participants and policies.

<table>
<thead>
<tr>
<th>Policy</th>
<th>E1</th>
<th>E2</th>
<th>E3</th>
<th>E4</th>
<th>E5</th>
<th>E6</th>
<th>E7</th>
<th>E8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
<td>C</td>
<td>U</td>
<td>L</td>
<td>W</td>
<td>C</td>
<td>U</td>
<td>L</td>
</tr>
<tr>
<td>WorkCloud</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PersonalCloud</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>WorkEmailApp</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PersonalEmailApp</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>SocialApp</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>18</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>3</td>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

*Five incorrect predictions for E8 (i.e., 3 in PersonalEmailApp and 2 in WorkEmailApp) are not included in the table due to insufficient information.*