Preference Discovery in Large Product Lines

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Abstract—When AI tools can generate many solutions, some human preference must be applied to determine which solution is relevant to the current project. One way to find those preferences is interactive search-based software engineering (iSBSE) where humans can influence the search process. Current iSBSE methods can lead to cognitive fatigue (when they overwhelm humans with too many overly elaborate questions). WHUN is an iSBSE algorithm that avoids that problem. Due to its recursive clustering procedure, WHUN only pesters humans for $O(\log_2 N)$ interactions. Further, each interaction is mediated via a feature selection procedure that reduces the number of asked questions. When compared to prior state-of-the-art iSBSE systems, WHUN runs faster, asks fewer questions, and achieves better solutions that are within 0.1% of the best solutions seen in our sample space. More importantly, WHUN scales to large problems (in our experiments, models with 1000 variables can be explored with half a dozen interactions where, each time, we ask only four questions). Accordingly, we recommend WHUN as a baseline against which future iSBSE work should be compared. To facilitate that, all our scripts are online at https://github.com/ai-se/whun.

Index Terms—Interactive Search-based Software Engineering, Project Management, CNF Reasoning, Cognitive Load Reduction

1 INTRODUCTION

When models are too complex, AI tools can be of great assistance. For example, the SCRUM model offered by Mendonca et al. [11] has 128 project management options and nearly 300 constraints (e.g., if sprints last two weeks, then each individual task must take less than 10 days of programming). Those constraints are so complicated that less than 1% of the $2^{128}$ possibly choices are acceptable to that model. When reasoning about this large space of constrained options, AI tools can be very useful. For example, the PicoSAT [2] theorem prover can find tens of millions of satisfying solutions to the SCRUM model.

But now we have a new problem: too many solutions. When PicoSAT finds millions of solutions, human preferences must be applied to find which solution is more acceptable for the current project. One way to find those preferences is interactive search-based software engineering (iSBSE) where humans can influence the search process [3]. iSBSE is a very active area of research (see examples in Table 1).

Current iSBSE methods face many challenges including cognitive fatigue (when they overwhelm humans with too many overly elaborate questions). Worse, as discussed below, those methods have issues with scalability and effectiveness (since the heuristics used to prune questions can also miss important candidate solutions).

Prior work in SE data mining [4, 5, 6, 7, 8, 9, 10, 11, 12] reports that AI tools do not require reasoning over all available data. This paper checks if those methods can improve iSBSE. Our WHUN algorithm (short for “What U Need”) uses a theorem prover to extract candidate solutions from models expressed in conjunctive normal form. Next, our recursive bi-clustering algorithm prunes half the candidates at each level of recursion. Finally, some entropy-based feature selection culls away uninteresting questions.

We note that this is a novel approach to iSBSE in that instead of patching (e.g.) a genetic algorithm with some secondary process, we replace the search device with data mining tools that know how to find minimal models. One reason to prefer this approach over other iSBSE tools [13] is that our method is not specific to some specific kind of model. Any model that can be reduced to conjunctive normal form can be processed by WHUN.

To assess this novel approach, we explored various product line models (SCRUM, online billing, and others). Compared to the prior state-of-the-art [14], WHUN found solutions using far fewer questions to the user. In those experiments, WHUN could handle 1000 variable models with less than half a dozen interactions where, each time, we ask only three questions (median).

The rest of this paper describes the background to the work, the WHUN algorithm, the product line models we used to test WHUN, and the experimental rig used in this analysis. Based on that experience, we conclude:

For better iSBSE, instead of patching an existing search-based algorithm, use data mining as a pre-processor to focus the subsequent search within the set of learned human preferences.

In this work, the focusing aspects of WHUN was seen to be particularly useful. Since we are reasoning over a reduced space (rather than all the candidate solutions), WHUN can explore tens of thousands of possible solutions for models with 100+ variables via just a few questions to the user. Those solutions fell within 0.1% of the best solutions seen in our sample. Accordingly, we recommend WHUN as a baseline against which future iSBSE work should be compared.

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TABLE 1: 24 recent iSBSE papers (from Table 2).

|   | Requirements: | Analysis and design: | Code implementation: | Testing and verification: | Distribution and maintenance: | Prescriptive process model: | Other: |
|---|---------------|----------------------|----------------------|--------------------------|------------------------------|-----------------------------|--------|
| 1 | 14 15 16 17 18 | 19 20 21 22 23 24 25 26 | 27 | 28 29 30 | 31 32 33 34 35 36 | 37 | 38 |

2 Background

2.1 Quality Without a Name

It has been often noted that humans use ill-defined criteria to judge the value of some systems. Alexander [37] talks of "quality without a name"; i.e. the ill-defined criteria used by humans to recognize a "good" system. Similar concepts can be found in the design pattern community [38] (see the work exploring "design bad smells" [39]).

This effect can be explained in many ways including (a) human cognitive theory and (b) the mathematics of decision making. Larkin and Simon [40] make the cognitive argument that experts "compile" their knowledge into fast-acting situation-reaction pairs that make their knowledge fast to apply, but hard to access and explain.

As to the mathematics of decision making, within N variables, there are sets of k interacting variables. For humans to pre-specify their preferences over that space, they would need to comment on all pairs of \( \binom{N}{2} \) effects. For our SCRUM model with \( N = 128 \) and \( k = 3 \) (say), \( \binom{128}{2} = 341,376 \). Give the sheer size of this task, it is not surprising that humans may have not considered all these options (which would explain why some of their opinions on these options are ill-defined).

Whatever the explanation (cognitive or mathematical), the knowledge acquisition literature [41] comments that humans are better at critiquing specific examples than articulating general principles. The advice from knowledge acquisition researchers [42] is that, to gain knowledge about a system, show humans some specific example and let them say "well, maybe not since...".

Hence, this paper (and much of the iSBSE community), takes the following approach. Rather than asking users to pre-specify their preferences, some part of a system is configured and presented to users for their comment. That comment is then used to guide the subsequent search.

That search process can be implemented using the search-based SE methods described below.

2.2 Search-based SE

In this paper, a model describing a space of options (e.g. for configuring a SCRUM project) is searched for valid choices. One complexity of such a search is that in any engineering discipline, including software engineering, it is common to trade-off between multiple competing goals. For example:

- For requirements engineers, we might find the least cost mitigations that enable most requirements [43].
- For project managers, we can explore software process models to find options that deliver more code in less time with fewer bugs [44].

For developers, we might tune data miners looking for ways to find more bugs in fewer lines of code (thereby reducing the human inspection effort required once the learner has finished [45].

Search-based SE (SBSE) is an automatic method for exploring that trade-space [46]. Unlike traditional optimization methods (e.g. SIMPLEX [47], search-based SE makes no assumption that all goals are achievable. Instead, search-based SE makes the more realistic assumption that to win on some goals might mean trading off on other goals.

SBSE is a very active area of research. Recent papers in this arena have explored many issues including project management with tools for software effort estimation [48, 49, 50, 51, 52, 53, 54, 55, 56, 57], and managing human resources [58]; requirements optimization [43, 59]; software design with tools for software architecture optimization [60] and extraction of products from very large product lines [57]; software security and intrusion detection [61, 62]; software quality with tools for software detect prediction [63, 64, 65, 66, 67, 68, 69] and test case generation [70]; software configuration [71, 72, 58]; text mining with tools for reasoning about StackOverflow [73, 74]; topic modeling [74, 75]; defect reports [74], and software artifact search [76].

There are many ways to do SBSE and this paper adopts the "oversampling" methods from Chen et al. [77]. That work compared two approaches to optimization:

- A traditional approach that mutated (say) \( 10^2 \) individuals across (e.g.) \( 10^2 \) generations;
- An oversampling approach that filled the first generation with \( (10^2)^2 = 10,000 \) individuals, which are then (a) recursively clustered and then (b) pruned by removing sub-trees whose roots are dominated by their nearest neighbor.

In studies with optimizing decisions within product lines, Chen et al. were able to show that such oversampling found solutions as good, or better, than the traditional approaches. This is a natural approach for WHUN since:

- Chen et al. also based their empirical work on software project lines;
- Also, as mentioned in the introduction, our problems start with theorem provers like PicoSAT overgenerates a large number of candidate solutions.

2.3 Interactive Search-based SE

One issue with standard SBSE is that all its conclusions are "black-box"; i.e. these algorithms run and produce results, even if users have no understanding or input into how those results are obtaining. Interactive SBSE is a variant of SBSE that tries to include humans in the reasoning process. More specifically, given a range of options, iSBSE tries to find which preferences are most important to users.

One question we are frequently asked is "should AI ignore human preferences lest those preferences force optimizers into some sub-optimal region of the total space?". In reply, we point out that this has not been the experience of the iSBSE field. The usual result is that competitive optimization results can be achieved while also respecting user preferences. Certainly, there are limits.
to adopting all user preferences. But one of the more interesting results shown below is that we can respect user preferences within our product lines, while still achieving optimization results that are within 0.1% of the best in our sample.

A little mathematics offers one explanation why this might be so. In the experiments below, in the SCRUM model, our algorithms select 20 preferences with a space of 128 boolean variables. That is, the space acceptable to our important user preferences fall within one-trillionth of the decision space. iSBSE can respect human preferences while still achieving good optimization results since even with all those preferences set, there are still 1 \times 10^{12} options available to the optimizer.

This fraction $2^{20}/2^{128}$ also explains why iSBSE should be seen as an essential part of human+AI decision making:

- iSBSE is essential to human-AI interaction since it stops human preferences being ignored.
- To see this, recall the fraction $2^{20}/2^{128}$ of important preferences within our SCRUM model. When the important user preferences fall within one-trillionth of the total space then without iSBSE, it is vanishingly unlikely that a fully automated algorithm will select those the options that matter to the oracle.

For all these reasons, we explore iSBSE. Table 2 offers an overview of current iSBSE research. To build that table, we started with a prominent paper in that area: specifically, the TSE’19 paper by Ramirez et al. [3]. Then we explored all the papers referenced by that paper or all subsequent papers that referenced it. This set was pruned to those that proposed methods for interactive search in search-based software engineering. This yielded the 24 papers of Table 2. Some details on those 24 papers are shown in Table 3.

The rest of this section reviews that research, using one exemplar research paper per row of Table 5. We will say many current iSBSE methods have issues with:

- Cognitive fatigue;
- Scalability;
- Effectiveness.

iSBSE methods can lead to cognitive fatigue when they overwhelm humans with too many overly elaborate questions. Standard SBSE methods generate and review thousands to millions of options via a process of mutation, crossover, and selection (repeated for dozens to hundreds of generations). Humans cannot quickly and accurately review that much material. Valerdi [78] reports that his panels of experts required three meetings (three hours each) to reach convergence on the influence of 10 variables on 10 examples (in the domain of cost estimation). Hence, according to Valerdi, it would be unreasonable to expect humans to quickly assess (e.g.) 128 options in a SCRUM model.

Many of the iSBSE methods in Table 2 implement Takagai’s advice. In summary, given some logs of the

| ID | Single Objective | Multi-objective | Many-objective | Other | Example system |
|----|------------------|-----------------|----------------|-------|---------------|
| 1  | Exact            | 4.1%            | 0%             | 0%    | 0%            |
| 2  | Metaheuristic    | 4.1%            | 0%             | 0%    | 0%            |
| 3  | Single-solution based | 4.1% | 0% | 0% | 0% |
| 4  | Evolutionary computation | 61.5% | 20.5% | 4.1% | 4.1% |
| 5  | Swarm intelligence | 8.3% | 0% | 0% | 0% |

TABLE 2: Overview of iSBSE research. Technique is indexed based on the IDs of Table 3. P-Type (Problem type) is indexed based on the IDs of Table 1.

TABLE 3: Note: Search Techniques Seen Used in iSBSE.
decisions made so far, iSBSE infers what possibilities can be ignored. As shown by the left-hand-side column of Table 2, there are many ways to do this. For example, Palma et al. use a state-of-the-art constraint solver (the MAX-SMT algorithm as a sub-routine inside ISBSE). We call this approach “exact” since it explores all solutions to a requirement model expressed as a set of constraints via extensive user interaction ($I = 25$ to $100$). In their method, they elicit pairwise comparisons of partial model solutions to decrease their “uncertainty” value about the final proposed solution. The decisions made by humans in evaluating these pairs of characteristics adjust elements of the problem formulation on their optimizer which guides it towards a better solution. While an interesting approach, we note that Palma et al. seem nervous about the scalability of their methods. The biggest model they ever report processing has 50 variables while, as shown below, we report results within a 1000-variable model.

Even if humans felt they could comment on (e.g.) 128 options, can we trust their assessment? Shackleford et al. warn that humans’ cognitive fatigue leads to errors in human decisions about what variables are most influential. Takagi notes that human cognitive fatigue can be decreased by

- Reducing $I$, the number of interactions (where, at each interaction, we ask the user questions)
- Reducing $S$, the size of questions per interaction

As to other iSBSE methods from Table 2 Lin et al. presented a “single solution based” method for code refactoring tasks. Their method Refactoring Navigator (RN) calculates and recommends refactoring “paths” from the starting point to the target, each path being a sequence of atomic refactorings. The user examines the recommended steps and can accept, reject or ignore them interactively. These interactions will then be used as feedback to calculate the next recommendation. The concept of $S$, in this case, represents how many different refactorings, and the size of each refactoring, a user has to evaluate at each interaction. Like Palma et al., Lin et al. are cautious about the scalability of their methods. In their threats to validity, they are unsure if their approach would generalize to larger systems from other domains.

Araújo et al. use the evolutionary computation architecture of Figure 1. This architecture combined an interactive genetic algorithm with a machine learner. Initially, humans are utilized to evaluate examples. But once there are enough examples to train a learner, Araújo et al. evaluate candidates via the learner’s recommendations. Their approach starts with a user setup of the optimization goal (e.g. how many generations it should run for and the number of human interactions the user wishes to perform). This number needs to be large enough to allow for the learning model to converge.

This process of Figure 1 continues until the number of human selected interactions is reached, after which the Learning Model is trained and steps instead of the human. Their algorithm shows the user the entire individual for evaluation, which is then given a numerical answer. This answer is then included in the formula for calculating the fitness of an individual.

Ferreira et al. proposed a “Swarm intelligence architecture” based on Araújo et al. where the user input their preferences on a particular model for each of the features of the model. The algorithm then changes its search approach on the feature space and provides the user with a candidate solution. On each interaction, the user can either accept the solution, where the algorithm terminates or they can reset their preferences for each of the features of the model to query for a different solution.

Another issue with current iSBSE methods is that there have issues with effectiveness. Sometimes, the heuristics used by the above methods result in fewer questions to the user, but also worse solutions. For example:

- Ferreira et al. report their methods to achieve a decrease of the maximum performance score of 13% on average in their experiments on the 50 feature model, reaching 13% of the best solutions generated by their methods.

When reasoning about a model with many constraints, most of the computational time of the model will be spent generating and evaluating solutions that might not hold to all of the constraints. As said by Hsu et al. one of the main causes of human fatigue is the fact that there are occasions where the result preferred by the user does not exist in the search space. Subjecting humans to possible evaluations on invalid solutions can also contribute to this factor for human fatigue.
Another comment on the other tools is that many iSBSE methods are “hard-wired” to the task at hand (e.g., Lin et al. [13]’s tool works specifically for refactoring models). Hence, when for our experiments, we prefer the generality of the Araújo et al. [14] approach.

Apart from generality, there are two other reasons to focus on the methods of Araújo et al.:

- As shown in Table 2, Araújo et al. is part of the evolutionary computation group, which represents the majority of prior work. Hence, by comparing WHUN with Araújo et al., we are comparing the standard iSBSE methods seen in the literature.
- Araújo et al. comment that their approach might be general enough to handle the software product lines we use in this study. They write “(Our) conceptual architecture can be considered sufficiently generic to be adopted in other software engineering scenarios tackled by SBSE, such as feature selection in software product lines...” [14].

Accordingly, in the following, to baseline WHUN against other methods, we will use Araújo et al. [14].

### 2.4 Software Product Lines

To evaluate WHUN, we require some prior state-of-the-art tool (e.g. Araújo et al.) as well as a set of models to explore. For this case study, we will use several software product lines (SPL) describing (a) SCRUM process options within an agile software projects; (b) an online billing system; and (c) several other models as well.

Rocha and Fantinato [84] comment that product lines are a generalization of the SPL architecture design for business process management. Kang’s feature models [85] are often used to represent a product line. That representation combines in a tree of features and constraints defining the multiple legal variations of a product [86]. For example, Figure 2 shows such a tree of options for a simple cell phone. If expressed in CNF (conjunctive normal form), that same model can be expressed as per Figure 3a.

Tools like the PicoSAT theorem prover take CNF formula expressed in the Dimacs format of Figure 3b, the output variable settings that satisfy the model constraints. A standard strategy (used by PicoSAT) is that, after one solution is found, its negation is added back to the model...
and the theorem prover is rerun to find something other than the prior solution. As a very simple model, the phone model contains only 14 possible solutions and they are instantly found by PicoSat in Figure 3c. Each solution is a valid product extracted from a product line like Figure 2.

(Technical aside: There can be a large “expansion factor” between models like Figure 2 and their associated CNF. Such models contain “implicit constraints”: e.g., all the mutually exclusions, all the valid multiplicity cardinalities, etc. Once all these implicit constraints are accounted for, a model can grow very complex indeed. For example, our SCRUM has only 7 explicit constraints by nearly 300 other implicit constraints.)

Figure 4 shows Mendonca et al.’s model of options within SCRUM projects. This model was written using information from Schwaber et al.’s Scrum Guide [87]. SCRUM is defined as a lightweight framework that helps organizations to deal with complex problems through adaptive solutions [87]. The model is comprised of options detailing the structure of the Development Team as well as their roles in the project. It also includes the configuration of various SCRUM activities and artifacts. The contains many mandatory features, focusing the selections further down the leaves. The cross-tree constraints create a very complex environment that rules out many possibilities. Specifically: less than 1% of the $2^{128}$ possible projects satisfy those 256 constraints.

One important aspect about product lines is that they are not “one-size-fits-all” models. Rather they are a large space of options from which users can design their preferred product. For example, based on our analysis with the PicoSAT theorem prover, we can assert that Figure 4 contains at least tens of millions of valid ways to configure a SCRUM project.

That said, once a theorem prover can generate a vast number of solutions from a model, then some secondary process must help users to navigate all those options.

2.5 Data Reduction

One way to navigate a large space of options is to use data mining. Levina et al. [88] comment that the reason any data mining method works is that data embedded in many dimensions can be reduced to a more compressed space without major information loss. In theory, this approach could improve iSBSE in two ways:

- Cognitive overload is reduced when users and iSBSE are exploring a reduced data space.
- iSBSE scales better when most data is irrelevant (and is removed via data compression).

There is much support for the Levina et al. conjecture. Numerous AI researchers report the existence of a small number of key variables that determine the behavior of the rest of the model [59]. Such keys have been discovered in AI many times and called many different names: Variable subset selection, narrows, master variables, and backdoors. In the 1960s, Amarel observed that search problems contain narrows; i.e. tiny sets of variable settings that must be used in any solution [89]. Amarel’s tools ignored much of the search space and just leap quickly from one narrow to another. Later, in the 1990s, Kohavi and John reported trials in data sets where up to 80% of the variables can be ignored without degrading classification accuracy [90]. At the same time, researchers in constraint satisfaction found “random search with retries” was a very effective strategy. Crawford and Baker reported that such searches took less time than a complete search to find more solutions using just a small number of retries [91]. Crawford and Baker explain the success of this strange approach by assuming models contain a small set of master variables (a.k.a. keys) that set the remaining variables. A similar conclusion comes from the work of Williams et al. [92]. They found that if a randomized search is repeated many times, then a small number of variable settings were shared by all solutions. They also found that if they set those variables before conducting the rest of the search, then formerly exponential runtimes collapsed to low-order polynomial time. They called these

![Fig. 4: The SCRUM Feature Model. Summary of the top level of the SCRUM feature model. The entire model, in XML format, is 166 lines long (see https://github.com/ai-se/whun/blob/main/SXFM/Scrum.xml). When translated into conjunctive normal form, all the disjunctions combine together to generate a large set of CNF clauses with hundreds of mutually exclusive feature settings. In all, the CNF version of this model has 128 options with 256 constraints.](image-url)
The oracle decides which features are preferred.

Maximum number of questions to ask at each point of the loop.

Initial number of generated solutions

Recursion stops when subtrees have less than \( t \) respectively, then computing

\[
\text{overlap}(a, p) = \frac{2\pi \sum_i |a_i - p_i|}{\sum_i \text{overlap}(i, p)}
\]

Each radius is then divided on the median \( \theta \) value into one of two clusters \( C_1, C_2 \) (for solutions with least and most \( \theta \)). These two clusters are then reviewed using the methods described above in §3.2.4.

3.2 Control Parameters

Table 4 list the control parameters for WHUN. The rest of this section explains each of those parameters.

In this paper, we show that the parameters of Table 4 can generate effective and smaller solutions than the prior state-of-the-art. Hence, while future work should vary these parameters, what we can say for now is that these current settings have some utility.

3.2.1 Samples

Samples controls how many of solutions WHUN generates using PicoSAT. Once generated, WHUN structures that space using a recursive biclustering algorithm (i.e. each level of recursion, divide the data into two groups, then recurse on each group). This generates a tree, where each node contains multiple solutions.

3.2.2 Enough

The recursive biclustering repeats until leaf clusters have less than enough solutions.

3.2.3 Pruning

The pruning function inputs the tree (generated above) and outputs a smaller tree that contains decisions that do not contradict user preferences. During this function, the user is asked questions. In order to minimize the number of times we ask the user questions, we use the tools of §3.2.4.

What the user does not know is that answer is being used of WHUN to evaluate and prune the two children of a node in the tree. The user’s answers are used to:

- Prune all the solutions in one of the sub-trees;

- Within each radius, each solution gets assigned an angle \( \theta \) according to its overlap with the pivot

### Table 4: Control options for WHUN.

| Setting   | Default | Notes                                      |
|-----------|---------|--------------------------------------------|
| sample    | 10,000  | Initial number of generated solutions      |
| enough    | \( t \) | Recursion stops when subtrees have less than enough items. |
| pruning   | function| Decide which nodes be used for the next question, collect that answer, delete any thing that contradicts that answer. |
| best      | 6       | The algorithm terminates when there are no longer nodes or features that we can ask questions on. |
| stop      | ‘good’  | The oracle decides which features are preferred. |
| oracle    | function| When recursion terminates, a domain-specific select function is run over the surviving instances to return the preferred solution. |
| select    | function| A weighing function that weights domain-specific preferences against more general considerations. |
| \( \alpha \) | 1.5     | Number of random trials (used in evaluation). |
| \( t \)   | 20      |                                             |

The recursive biclustering repeats until leaf clusters have less than enough solutions.

3.1 Clustering Binary Variables

Initially, we tried a simple Euclidean distance measure This performed poorly, especially as the number of features in the a model increased. All our data is non-numeric. In each solution, a feature is either selected or it is not, which we initially (and naively) modeled as with true=1 and false=0. This was incorrect since there is no meaning to (e.g.) 0.5.

For boolean variables, WHUN uses Chen et al. boolean radial distance metric \( \text{overlap} \). In this approach, solutions are recursively be clustered as follows. One solution is selected (at random) to be the “pivot”; All other solutions are divided in two (where the division point is the median distance of all points to the pivot). The algorithm then recurses on each division. In the Chen et al. approach, distance is calculated as follows.

- All solutions get assigned a “radius” equal to the count of how many “trues” appear in the solution.

### Table 4: Control options for WHUN.
• Prune some of the solutions in the other surviving sub-tree (those that contradict the answers), Pruning is applied repeatedly until the stop criteria of §3.2.5 is satisfied.

Once pruning terminates, the remaining solutions are searched for those that maximize (or minimize) the domain goals. For more on that process, see §3.2.7

### 3.2.4 Best

Best controls how many questions (at most) are asked at each loop of the algorithm. WHUN ranks all the features and nodes of the remaining tree at some point in the loop using four heuristics:

- Refraction;
- Entropy;
- Depth of first difference;
- Differences.

If more than one feature has a maximum rank, then WHUN selections up to best maximum scoring features, at random. In practice:

- At the start of the loop, WHUN asks the maximum number of questions.
- Deeper down, that number decreases down to one.

Refraction just says “never ask the same thing twice”. Each feature $f_i$ is assigned a value $\text{asked}[f_i] = 0$ (initially) and then $\text{asked}[f_i] = 1$ if we ask the user about whether or not to use that feature.

The same is done about individual nodes in the tree. With each of them being assigned the same value $\text{asked}[n_i] = 0$ (initially) and then $\text{asked}[n_i] = 1$ if we query the user on that particular node.

Entropy is a measure of the variability of a symbolic distribution [94]. At each point of the loop, the subset of $N$ remaining candidate solutions at that point mentions feature $F = f_1, f_2, \ldots$ which, in turn, have settings true or false at frequencies $n, N - n$ respectively. The entropy of each feature is a measure of the effort required to recreate that distribution; i.e.

$$e[f_i] = - \left( \frac{n}{N} \right) \log_2 \left( \frac{n}{N} \right) - \left( \frac{N - n}{N} \right) \log_2 \left( \frac{N - n}{N} \right)$$

The feature with maximum entropy $e$ is the one which, if we decide to use, will exclude the most number of remaining solutions.

Depth of first difference is a measure of how early in our tree-like structure a certain feature differs in the sub-trees in the subset of $N$ remaining candidate solutions, of a symbolic distribution [94]. At each point of the loop, The depth of each feature is a normalized count of the first difference of that given feature on the tree i.e.

$$d[f_i] = \frac{\text{depth}[f_i]}{\text{cur_tree}}$$

The feature with minimum depth $e$ is the one which, if we decide to use, will exclude the largest number of remaining sub-trees.

Differences: WHUN is through it’s loop dividing the tree of solutions into smaller sub-trees of similar solutions. This means that, as the loop goes deeper, WHUN is working on solutions with increasingly similarity; i.e fewer features will have different settings in remaining candidate solutions found at each level of the loop. WHUN exploits this effect as follows. First WHUN ranks all the features in order to select for which features will be asked at that point in time through the following equation:

$$\text{good}_f = e[f_i] * (1 - d[f_i]) * (1 - \text{asked}[f_i]) \quad (1)$$

Let $\Delta[f_i] = 1$ if some feature has different settings in the representatives of each side a given surviving node (and zero otherwise). To select a the most relevant node to ask at each level of the loop, WHUN selects the node that maximizes:

$$\text{good}_n = \frac{\sum |f| (\Delta[f_i] * \text{good}_f) * (1 - \text{asked}[n_i])}{\sum |f| \Delta[f_i]} \quad (2)$$

Note that good evaluates to zero if a node or a feature has been asked = 1 or in the case of good$_n$, if there is no difference in its setting between the two sub-trees.

### 3.2.5 Stop

The loop repeats until the algorithm runs out of interesting nodes or features to ask, i.e. both good methods return 0 for the entire remaining set of candidate solutions.

### 3.2.6 Oracle

The eventual goal of iSBSE is to help humans as they serve as oracles (that evaluate solutions). That said, it is common practice in the research literature, when commissioning a new iSBSE rig, to use non-human surrogate oracles to assess new iSBSE algorithms. Such artificial oracles are required since no human would submit to the number of experiments required for the commissioning process.

To see why that is so, consider the experiments required for this paper. Due to the stochastic nature of our algorithms, we must rerun it with different random number sees. In all, our experiments were run for two algorithms (WHUN and Araujo et al. [14]) 20 times for each of the models. Worse yet, we needed to run, multiple algorithms, repeat our experiments 20 times (for statistical validity). We estimate that we ran our system 500+ times (each time asking about dozens to hundreds of variables).

To make that possible, we used an artificial oracle that could comment on which features are preferred. For each of our 500+ runs, if the oracle is asked about feature $f_i$, then it will pick true or false at random, then cache that decision (for the remainder of that run). The questioning process for humans would require a prior augmentation of the data by inserting human-readable descriptions or clarifications to feature names when needed. Those would be used in place of the variable name in order to show the user which variables he is selecting in a more user-friendly way.

In the baseline algorithm, the oracle is initialized with a set of values for each feature in the SCRUM feature model which are then normalized to add up to 1. When given a candidate solution, the oracle then calculates the answer with these values.
3.2.7 Select

When all the above terminates, the initial tree of solutions is now much smaller (since many of the decisions that contradict user preferences have been removed).

The surviving solutions are then sorted a select function that comments on how well each solution satisfies domain goals. For example, for the product line case studies, we use Equation 3

\[
select = |C|^2 + |D|^2 + \alpha(1 - HPPS))^2 + |(1 - P)|^2 \tag{3}
\]

Here HPPS is the Human Preference Percentage Score, or the percentage of human prioritized features the solution contains. As to the other variables, we use the experimental methods of other product line researchers such as Sayyad et al. [4] and Henard et al. [95]. In that work, the Dimacs representation is augmented with we generated vectors storing extra information about each feature:

- \( D \): a defect variable representing the existence of such defect being a random boolean (0 or 1). This variable represents whether bugs were seen in prior products that used this feature.
- \( C \): a cost counter ranging from 0 to 10 representing the prior effort seen when this feature was added to prior products;
- \( P \): a precedence variable representing how often this feature was successfully used in previous products, it also being a random boolean (0 or 1).

For each of the features the values for \( D, C \) and \( P \) are generated once per start of each run, which means that they are consistent throughout the entire search space of valid solutions.

3.2.8 \( \alpha \)

In Equation 3 the \( \alpha \) term weighs domain-specific considerations like \( D, C, P \) against more general considerations such as good (from Equation 1). After Araújo et al. [14], we use \( \alpha = 1.5 \) since that means that general considerations (about good) weights our decisions about half as much as the other three domain-specific parameters \( D, C, P \).

4 METHODS

This section discusses the methods and techniques used throughout the experiment, as well as the origins and characteristics of the feature model.

4.1 Feature Models

This study used ten features models, all from the SXFM SPLIT-Research web site:

- A Billing feature model that discusses methods for banking billing, invoicing, and payment for online transactions. For more details on that model, see [2].
- The SCRUM feature model shown of Fig. 4 with 128 features and 256 constraints.
- Four artificially generated feature models (called 125 Feat, 250 Feat, 500 Feat and 1000 Feat) where the number of features was increased while the ratio of constraints to features was kept constant.
- Four more artificially generated feature models (called 0.25 C.D, 0.75 C.D, 0.50 C.D and 1.00 C.D) where the number of features was kept constant (at 500) while the ratio of constraints to features was increased.

The first model was selected to be small enough to support simple debugging. The second model was chosen to be large enough to stress our tools. The artificially generated models were chosen to check the generalities of our conclusions. These artificial models were generated using tools from the SPLIT-Research website.

All these models were taken from the SXFM format and converted into the Dimacs format using the FeatureIDE [96]. The Dimacs format is a standard interface to most SAT solvers.

4.2 Algorithms

WHUN is implemented in Python 3.8. That code is available at [3] That site contains CSV files listing tens of thousands of solutions to all our models. Those solutions were generated by PicoSAT v0.6.3 which installed via “pip3 install pycosat==0.6.3”.

For our baseline comparison, Araujo et al. do not offer a reproduction package for their work. Hence, we reimplemented their code based on the description [4].

As to the tools used in artificial model creation, these are available at the SPLIT-research site [5].

4.3 Statistical Methods

In our study, we report median and interquartile ranges (which show 50th percentile and 75th-25th percentile), of the number of interactions and the scores for our entire experiment. We collect median and interquartile range values for each of the projects.

To make comparisons among all algorithms on a single project, we implement the Scott-Knott analysis [97]. In summary, by using Scott-Knott, algorithms are sorted by their performance. After that, they are assigned to different ranks if the performance of the algorithm at position \( i \) is significantly different to the algorithm at position \( i - 1 \).

To be more precise, Scott-Knott sorts the list of experiments (in this paper, WHUN and Araujo et al. for each of the ten datasets) by their median score. After the sorting, it then splits the list into two sub-lists. The goal for such a split is to maximize the expected value of differences in the observed performances before and after division [98]. For example, in our study, we implement two different algorithms within four sample solutions spaces of the scrum model in list \( l \) for a total of 8 experiments, then the possible divisions of \( l_1 \) and \( l_2 \) are \( (l_1, l_2) \in \{(1, 7), (2, 6), (3, 5), (4, 4), (5, 3), (6, 2), (7, 1)\} \). Scott-Knott analysis then declares one of the above divisions

4. https://github.com/ai-se/whun
5. https://github.com/ai-se/whun/blob/main/BASELINE.ipynb
6. http://www.splot-research.org/
to be the best split. The best split should maximize the difference \( E(\Delta) \) in the expected mean value before and after the split:

\[
E(\Delta) = \frac{|l_1|}{|l|} |\text{abs}(l_1 - l)|^2 + \frac{|l_2|}{|l|} |\text{abs}(l_2 - l)|^2
\] (4)

where:
- \(|l|\), \(|l_1|\), and \(|l_2|\): Size of list \( l \), \( l_1 \), and \( l_2 \).
- \( l, l_1, \) and \( l_2 \): Mean value of list \( l \), \( l_1 \), and \( l_2 \).

After the best split is declared by the formula above, Scott-Knott then implements some statistical hypothesis tests to check whether the division is useful or not. Here “useful” means \( l_1 \) and \( l_2 \) differ significantly by applying hypothesis test \( H \). If the division is checked as a useful split, the Scott-Knott analysis will then run recursively on each half of the best split until no division can be made. In our study, hypothesis test \( H \) is the cliff’s delta non-parametric effect size measure. Cliff’s delta quantifies the number of differences between two lists of observations beyond p-values interpolation [99]. The division passes the hypothesis test if it is not a “small” effect (\( \text{Delta} \geq 0.147 \)). The cliff’s delta non-parametric effect size test explores two lists \( A \) and \( B \) with size \(|A|\) and \(|B|\):

\[
\text{Delta} = \frac{\sum_{x \in A} \sum_{y \in B} \begin{cases} +1, & \text{if } x > y \\ -1, & \text{if } x < y \\ 0, & \text{if } x = y \end{cases} }{|A||B|}
\] (5)

In this expression, cliff’s delta estimates the probability that a value in list \( A \) is greater than a value in list \( B \), minus the reverse probability [99]. This hypothesis test and its effect size is supported by Hess and Kromery [100].

### 5 Results

Due to the stochastic nature of our algorithms, we must rerun it with different random number seeds. In all, our experiments were run for two algorithms (WHUN and Araújo et al. [14]) 20 times for each of the feature models.

#### 5.1 Research Questions

Our results were used to answer the following research questions:

- **RQ1**: Does WHUN ask fewer questions than the prior state-of-the-art algorithm?
- **RQ2**: Compared to the prior state-of-the-art, how effective is WHUN at finding “good” solutions?
- **RQ3**: How well does WHUN scale?

Note that we applied the statistics of §4.3 to all the following conclusions. In summary, all the improvements seen with WHUN were very large indeed. Also, all these changes were found to be non-small and significant.

#### 5.1.1 RQ1: Does WHUN ask fewer questions than the prior state-of-the-art algorithm?

This is the core question of this research.

As shown in Figure 5a, compared to Araújo et al., WHUN goes the oracle six to 16 fewer times. Further, as shown in Figure 5b, compared to Araújo et al., when WHUN needs information from the oracle, it asks 29 to 333 fewer features. Hence we say, for the algorithms and models explored here, WHUN asks orders of magnitude less information from the oracle.

#### 5.1.2 RQ2: Compared to the prior state-of-the-art, how effective is WHUN at finding “good” solutions?

Here, “good” can be defined using the domain-specific select function of Equation 3. To do that we:

- Sort all the solutions generated by PicoSAT using Equation 3. This results in solutions ranked best to
• Find percentile rank $R_i$ as follows: Sort the solutions returned by WHUN using the same equation, then select the solution one. Rank that solution by finding its percentile place in the all sort.

• Find percentile rank $R_2$ of the Araujo et al. system using the same procedure, the difference is that we sort all based on all of the solutions generated by the interactive Genetic Algorithm.

Figure 6 compares $R_1$ in red and $R_2$ in blue. We note that WHUN finds solutions in the first one-hundredth of the first percent of all its solutions while Araujo et al.’s solutions rank much worse; i.e. in the top 1% to 36% (median = 7%) within any solution seen during its processing.

5.1.3 RQ3: How well does WHUN scale?

For completeness, we include the following results. Figure 7 shows the runtimes for WHUN (and Araujo et al.) as we increase model size (number of features) or internal complexity (number of cross tree constraints). While these results do not recommend WHUN over Araujo et al., it does show that iSBSE methods can somewhat scale to models of increasing size and complexity.

5.2 Other Issues

Apart from our research questions, we have other reasons to recommend WHUN over the methods of Araujo et al.

To understand the significance of the following, we first note that 100% of all the solutions explored by WHUN are valid. The reason for this is simple: we let PicoSAT generate valid solutions, then we down-select from that space.

Other iSBSE methods can generate far fewer valid solutions. Figure 8 shows what happens when we take the solutions generated by Araujo et al.’s genetic algorithm, then applied the constraints of the Dimacs models. As seen in that figure, most of the solutions generated by their methods are not valid (since their genetic algorithm did not use those constraints to build the new solution).

6 Threats to Validity

As with any empirical study, biases can affect the final results. Therefore, any conclusions made from this work must be considered with the following issues in mind:

Evaluation Bias - All the above results were obtained using automated oracles; i.e. no human oracle input. Our rationale for that approach was discussed at the start of §3.2.6. We note that the use of such automated oracles is a widely-used practice in the iSBSE field. In the papers reviewed in Table 2 most of them make use automated oracles, with less than half utilizing only humans. And when humans are utilized, they can only manually review very small models (due to issues of cognitive overload).

Sampling Bias - This threatens any empirical study using datasets. i.e., what works here may not work everywhere. For example, we have applied WHUN to two real-life models of different software product lines coupled with eight randomly generated models with different characteristics.
to mitigate Sampling Bias. However, the behavior of WHUN to monumental larger models (i.e. hundreds of thousands of features) still needs to be evaluated.

**Parameter bias** - There are a high quantity of parameters that control the inner workings of WHUN. While this work shows that the selected parameters on Table 4 are capable of generating effective and smaller solutions than prior state-of-the-art. We believe that future work on the variation on these parameters may prove to give better results. That said, in defense of our current settings, we note that we can find solutions with 0.1% of the best seen in our sample.

**Algorithm bias** - To the best of our knowledge the selected baseline from Araújo et al. [14] was the only available iSBSE tool generic enough to be used as a comparison against WHUN. An adaptation of WHUN to more niche problems in the iSBSE field may prove to be fruitful from a comparison standpoint.

## 7 Conclusion

When AI tools find millions of solutions, human preferences must be applied to find which solution are acceptable for the current project. In theory, iSBSE methods can offer assistance for this problem. But the current generation of iSBSE methods may not scale to large models due to issues of cognitive overload and algorithm scalability. The size of the models.

If the problem is "too many possibilities" then solution might be "prune the possibilities". Here we apply some data mining methods (recursive biclustering, entropy feature weighting) which, to the best of our knowledge, have not been explored before in the iSBSE literature.

Preexperimentally, we were worried that pruning the regions that violate user preferences could also cull options that were essential to the optimization. For the models studied here, this tuned out not to be the case. Compared to the prior state-of-the-art (Araújo et al. [14]), WHUN performed very well indeed:

- As shown in Figure 5, WHUN asks orders of magnitude fewer questions than Araújo et al.
- In all our runs, WHUN was able to find solutions within 0.1% of the best solutions seen in our samples. Araújo et al., on the other hand performed far worse (see Figure 6).
- While 100% of WHUN’s solutions are valid, very few of the solutions found by Araújo et al. satisfied model constraints (see Figure 5).

Hence we recommend:

> For better iSBSE, instead of patching an existing search-based algorithm, use data mining as a pre-processor to focus the subsequent search within the set of learned human preferences.

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