Abstract—Can we simplify explanations for software analytics? Maybe. Recent results show that systems often exhibit a “keys effect”: i.e. a few key features control the rest. Just to say the obvious, for systems controlled by a few keys, explanation and control is just a matter of running a handful of “what-if” queries across the keys. By exploiting the keys effect, it should be possible to dramatically simplify even complex explanations, such as those required for ethical AI systems.

I. INTRODUCTION

Sometimes, AI must be explainable. If some model learned by an AI is to be used to persuade someone to change what they are doing, it needs to be explainable such that humans can debate the merits of its conclusions. Tan et al. [1] argue that for software vendors, managers, developers and users, explainable insights are the core deliverables of analytics. Sawyer et al. comment that explainable (and actionable) insights are the key driver for businesses to invest in analytics [2].

Recently, the requirements for explainable AI have become quite complex. The European Union, Microsoft, and the IEEE have all released white papers discussing ethical AI [3]–[5]. While these documents differ in the details, they all agree that ethical AI must be “FAT”; i.e. fair, accountable and transparent. Such “FAT” systems support five “FAT” items:
1) Integration with human agency;
2) Accountability, where old conclusions can be challenged;
3) Transparency of how conclusions are made;
4) Oversight on what to change so as to change conclusions;
5) Inclusiveness, such that no specific segment of society is especially and unnecessarily privileged or discriminated against by the actions of the AI.

This list may seem like a complex set of requirements for explainable ethical AI. However, as seen in this paper, software systems often have a “keys effect” by which a few key features control the rest. Just to say the obvious, when systems are controlled by a few keys, then explanation and control is just a matter of running a few “what-if” queries over the keys. The rest of this paper discusses (a) how to implement the five “FAT” items; and (b) how the keys effect simplifies all those implementations.

II. BUT FIRST, WHAT IS “EXPLANATION”?

Cognitive science argues that models comprising small rules are more explainable. Larkin et al. [6] characterize human expertise in terms of very small short term memory, or STM (used as a temporary scratch pad for current observation) and a very large long term memory, or LTM. The LTM holds separate tiny rule fragments that explore the contents of STM to say “when you see THIS, do THAT”. When an LTM rule triggers, its consequence can rewrite STM contents which, in turn, can trigger other rules. Short term memory is very small, perhaps even as small as four to seven items [7], [8].

Experts are experts, says Larkin et al. [6] because the patterns in their LTM dictate what to do, without needing to pause for reflection. Novices perform worse than experts, says Larkin et al., when they fill up their STM with too many to-do’s. Since, experts post far fewer to-do’s in their STMs, they complete their tasks faster because (a) they are less encumbered by excessive reflection and (b) there is more space in their STM to reason about new information.

First proposed in 1981, this theory still remains relevant [1]. Humans best understand a model which can “fit” it into their LTM; i.e., when that model comprises many small fragments. Phillips et al. [10] and others [11]–[13] discuss how models containing tiny rule fragments can be quickly comprehended by doctors in emergency rooms making rapid decisions; or by soldiers on guard making snap decisions about whether to fire or not on a potential enemy; or by stockbrokers making instant decisions about buying or selling stock. This theory-of-small-fragments explains both expert competency and incompetency in software engineering tasks such as understanding code [14]. Specifically, expert-level comprehension means having rules that quickly lead to decisions, without clogging the STM.

It can be hard to find small transparent chunks of knowledge in large data sets. To some extent, FFTrees [10], LIME [15], and SHAP [16] addresses that problem. But a recent literature survey by Peng et al. [17] shows that current explanation tools just rank the influence of features on single goals. Also, LIME and SHAP have two other limitations: they only show how single features effect single goals. Also they rely on randomly generated instances. Such instance creation can overlook important structural details (such as the keys effect, described below). The explanations generated in that way might be over- elaborate, or irrelevant [17].

Hence, we seek a better framework that (a) offers succinct explanations from conjunctions of multiple features on multiple goals; and which (b) understands the structure of the data.

III. WHAT ARE “KEYS”?

We have said in the introduction that the keys effect means a few key features control the rest. Another way to say the say

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1 Recently, Ma et al. [9] used evidence from neuroscience and functional MRIs to argue that STM capacity might be better measured using other factors than “number of items”. But even they conceded that “the concept of a limited (STM) has considerable explanatory power for behavioral data”.
thing is that most features in a system can be ignored or, more formally, a system with $N$ variables with $S$ values usually visits much less than $S^N$ states. This section discusses this “Druzdel effect” and shows how it impacts the number of key features that control a system.

Imagine, in Figure 1 that we discretize the horizontal and vertical features into ten equal-width bins. Once discretized in this way, then this data has $(S = 10)^{N=2} = 100$ states. But since the distribution of these features are skewed (particularly, the horizontal blue values), many of those states occur at zero frequency (evidence: see the white space in Figure 1).

This Druzdel effect (that most of the potential states within software are never visited) has been observed in practice. For example, Druzdel’s [18] logged the frequency of observed states in a medical diagnostic system that monitored anesthesia patients in intensive care. Of the 525,312 observed states, one state occurred over half the time; 49 states covered 91% of the probabilities; and the remaining states occurred vanishingly rarely (at frequencies ranging from $10^{-6}$ to $10^{-22}$).

One explanation for this Druzdel effect is that when code runs, it only visits the $v$ states approved by the combination of its internal logic – and this space can be far smaller that $S^N$ (so $v \ll S^N$). Explanations, or controllers, of software that visits $v \ll S^N$ states only need to explore $\log_2 v$ “key” features. For example, Zhang et al. report that by generating tests only for the main branches in the code, even applications that process large cloud databases can be tested via just a few dozen inputs [19].

The number of features in a data set can be inferred from the number of examples required to model that data; e.g.

- Druzdel found $v_1 = 49$ commonly reached states.
- Yu et al. [20] report that security violations in 28,750 Mozilla functions can be successfully modelled via an SVM with $v_2 = 271$ support vectors.
- Tu et al. [21] report that defect labelling in 6000 commits from Github can be successfully modelled via a SVM with $v_3 = 300$ support vectors [21].

Assuming binary features and that the number of key features is $N_i = \log_2 v_i$. Hence, the above systems could be controlled via $N_1, N_2, N_3 \approx 6, 9, 9$ key binary features.

### IV. Example

This sections shows a small example where keys find the tiny fragments of knowledge recommended by cognitive scientists.

Suppose an analyst wants to buy a fuel efficient lightweight car with good acceleration. The file auto93 (from the UC Irvine ML repository) has hundreds of examples of cars that mentions those features as well as number of cylinders $c$, horsepower $h$, displacement $d$ (a.k.a. size of car), year of release $y$ and country of origin $o$. From this data, we could apply (e.g.) linear regression to learn the model of Equation 1.

$$
\begin{align*}
\text{weight} &= 60.7 \times c + 5.2 \times d + 4.1 \times h + 13.7 \times y + -48 \times o + 234.2 \\
\text{mpg} &= -0.6 \times c - 0.1 \times d + -0.1a + 0.6 \times y + 1.2 \times o + -12.9 \\
\text{accel} &= 0.1 \times c + 0.1 \times d - 0.1a + 0.1 \times y + -0.2 \times o + 21.2
\end{align*}
$$

This model is not tiny chunks of instantly interpretable knowledge recommended by cognitive scientists. In order to make recommendations about what kind of car to buy, some further processing is required. For example, we could run a large number of what-of queries across a large population of cars. A standard tool for this purpose is a genetic algorithm that (a) mutates population of cars, (b) scores the mutants on the above three equations, then (c) selects the best scoring mutants as parents for the next generation of mutants. That genetic algorithm approach may not not scale to large problems. Peng et al. [17] has applied genetic algorithms to explore $C = 10^4$ software configuration options (in order to optimize for $G = 2$ goals). In that application, the $O(GC^3)$ non-dominating sort procedure of the NSGA-II [22] genetic algorithm took hours to terminate. A (much) faster approach, that generates tiny chunks of instantly interpretable knowledge, comes from assuming the keys effect, as follows.

- If features control the output, then it follows that those features, with different settings, appear in different outputs.
- Also, if those features are few in number, then they will be a small set of features with most effect on the results.

To say that another way, to exploit the keys effect, we only need to apply a little data mining. The follow three points describe a baseline keys-based algorithm called KEYS0. The algorithm assumes that there exists a small number of feature ranges that occur with different frequencies in desired and undesired outcomes. Hence, a little random sampling is enough to quickly find those keys.

1) **Randomly divide the data.** Select a few random points to find two distant points $P_1, P_2$ within the data. Sort them such that point $P_1$ is better than $P_2$ (if exploring multiple goals, use some domination predicate to rank the two items). Mark the data best, rest depending on whether it is closest to $P_1, P_2$ respectively.

2) **Look for feature ranges with very different frequencies in best and rest.** Divide numeric features into $\sqrt{n}$ sized ranges. Combine adjacent ranges that have similar best, rest frequencies. Rank feature ranges, favoring those that are more frequent in best than rest. Print the top-ranked range.

3) **Recurse.** Select the data that matches that top range (discarding the rest). If anything is discarded, loop back to step1.

When applied to the auto93 data, in 52ms, KEYS0 terminates in two loops after evaluating just four cars. KEYS0 prints...
two tiny chunks of instantly interpretable knowledge; i.e. the ranges “cylinders ≤ 4” and “origin==3”.

Figure 2 shows the position of the data selected by KEYS0. In a result consistent with the presence of keys within *auto93*, we see that by examining just four examples and Fairer Software Made Easier (using “Keys”) asking about two ranges, we can find a useful region in the data. Further improvements are possible, of course (e.g. the acceleration is still mid-range in the final selected data). Nevertheless, the things to note here is (a) how little we had to use the data in order to achieve such large improvements via tiny chunks of quickly interpretable knowledge; and (b) as far as we can tell, the model learned by KEYS0 is not apparent within the output of standard learners such as Equation 1.

**V. WHAT CAUSES KEYS?**

Menzies [23] speculates that keys arise from **naturalness** [24] and/or **power-law** [25] effects. Since programs exhibit the same frequent patterns seen in human language, then naturally we would expect that code usually contains a small number of structures, repeated many times [24]. As to power laws, suppose programmer2 most understands a small region of the code written by programmer1. That programmer would tend to make most changes around that region. If programmer3 does the same for programmer2’s code, and programmer4 does the same for programmer3’s code then that, over time, that team would spend most of their time working on a tiny portion of the overall code base [25]. In such natural code that is subject to those power laws, finding a controller for any part of the code would mean that we also have a controller for many other parts of the code (due to repetition, due to the small size of the maintained code base).

These effects are not just theoretical speculation– they have been seen in practice. Lin and Whitehead report power law effects they have observed in software [25]. Hindle et al. [24] report all the application work in software analytics that successfully exploits naturalness. Stallings [26] comments that the design of operating systems often assumes a **locality of reference**; i.e. that program execution does not dash across all the code all the time but instead is mostly focused on a small part of the memory or instruction space. Lumpe et al. [27] report studies tracking decades of work in dozens of open source projects. In that code base, most classes are written once, revised never. Also, most of the defect inducing activity is centered around a small number of rapidly changing classes. A similar pattern (where most activity is focused on a small part of the code base) has been reported in software from AT&T [28], NASA [29], and within some widely used open source compiler tools (GCC [29]).

**VI. EXPLOITING KEYS FOR ETHICAL AI**

Regardless of their cause, this section argues the keys effect can support the five “FAT” items listed in the introduction.

**Integration with human agency:** Figure 3 shows human+AI interaction. For example, **active learning** is where AI and humans team up to solve problems. Whenever humans make a decision about certain example, the active learner updates a model that predicts what humans might say about the next example. Once the AI can adequately predict the human’s opinion, then the human can retire and the AI can label the rest of the data. In Figure 3 one explanation system is better than another if it leads to higher \( z = \text{goals} \) are achieved with fewer \( y = \text{decisions} \).

We actually saw an example of Figure 3 in the above discussion. Yu,Tu et al. [20], [21] incrementally updated an SVM model based on an active learner. In a result consistent with the keys effect, they needed only a few hundred support vectors to model their data (Firefox security violations and the labelling of defect data in Github). We conjecture that this result could be improved even further (using fewer questions) by combining KEYS0 with the Yu,Tu tools.

**Accountability:** If we cache the y-axis decisions of Figure 3 then the decision process that leads to the current system can be replayed by a third party. For systems demonstrating the keys effect, then the total number of features that needs to be reviewed during an audit could be as low as \( \log_2 10^3 \) (see the calculations at the end of §III). While this might take days to weeks to study, such a manual audit is within the realms of possibilities by human beings. Further, if we cache the entire rig that generated Figure 3 then it would be possible to change some decision about the y axis, then replay the rest of the reasoning to see if that change effect the outcomes of the rest of the system. Finally, if some part of the Figure 3 needs to be entirely revised then the keys effect promises that that revision would not be an arduous process.

**Transparency:** One issue with integrating with human agency is cognitive overload. Humans and AI tools can cope with different amounts of data. AI tools can readily process \( 10^8 \) examples per minute, where example might contain \( 10^2 \) features, or even more [32]. Human reasoning, on the other hand, is not so scalable. While we cannot speak for all humans, this author asserts that reading \( 10^5 \) examples is just overwhelming. Hence we say that one explanation system is
Fig. 4. Algorithm with oversight authority can request changes that alter conclusions. In this example, the tree on the left has median number of defects per leaf. Using this structure, we can walk the tree looking for plans that change the conclusion from defects = 90% probable to defects = 10% problem (here, RFC, LOC, RBO are static code metrics that can be altered by different refactoring activities defined in Table 2 of [30]). In this example, there is historical data that RFC, LOC are never changed without also changing RBO. Hence, we would propose the right-hand plan since it has most precedent in the historical record. Example from [31].

more transparent than another if it shows the user less data; i.e if it does not lead to cognitive overload.

Here again, keys can be useful. Recall from §IV that we used keys to explore hundreds of examples with just two questions about two features. In an even more impressive example, Lustosa et al. [33] recently used a variant of KEYS0 to explore different options for managing an agile SCRUM project. That study explored 10,000 examples with 128 features by asking the user $y \leq 6$ questions (where each question mentioned only 4 ranges). Note that, once again, needing to control so few features is yet another example of how keys can simplify explaining/controlling a system.

**Human oversight:** Krishna et al. [31] argues we can learn how to change conclusions using (a) one algorithm that makes predictions; then (b) a second algorithm that reports the delta between regions with different predictions. His variant of KEYS0 recursively divide the whole data, without pruning any branches. Next, he computed the mean conclusion seen in each leaf. As shown in Figure 4, left-hand-side, we might prefer some leaf conclusions over the others (e.g. some leaves have a 90% probability of software having defects while other leaves predict a 0% probability of defects). In that case, we can walk the tree from worse to better conclusions, each time querying the data division rule at each node. If that process finds multiple ways to improve some conclusion then, as shown in Plan2 of Figure 4 we might prefer the plan with most precedence in the historical record. In a result consistent with the keys effect, for data sets with 20 features, the plans generated by this procedure only needs to change 2-4 features [30], [31].

**Inclusiveness:** there are many tests for checking if an AI tool is unfairly making conclusions at (e.g.) different false positive rates for different social groups. One way to repair an unfair learner is to change how that learner builds its model via hyperparameter optimization [34], [35]; i.e. planning to change the learner control parameters such that the (say) false alarm rates are adjusted. In such optimization, the nodes of the trees in Figure 4 would refer to control parameters of the learner while the leaves would be scored by (e.g.) the false alarm rates for the different social groups in the data. With those changes, the planning process described in Figure 4 could also be applied to unfairness reduction.

**VII. Discussion and Future Work**

We need to study explanation since explanation is the key to so much more; e.g., as shown above, controlling, classification, regression, planning, and optimization. As part of that study, we should also explore the keys effect since, as suggested above, those keys can simplify the generation of even complex types of explanations.

But keys does not solve all the problems of explanation and ethical AI. In fact, reviewing the above, we can see many open issues. For example, do all data sets have keys? Is there some graduated explanation algorithm that can shift easily from “keys mode” (for data sets with keys) to another mode (for other kinds of data)? KEYS0 currently divides data using a Euclidean distance metric. But what about other dimensions as synthesised by (e.g.) some neural autoencoder? Further, what happens to Figure 1 if humans make a wrong decision along the y-axis? How do we detect that mistake? Furthermore, what happens when teams work together yet team members have conflicting goals?

The above paragraph is just a short sample of the issues raised by our work on keys-as-explanation (for other issues and research challenges raised buy this article, see [http://tiny.cc/todo21]). In our experience, exploring keys-for-explanation, we often find more research questions than what we started with. But perhaps that is the true power of keys. Keys-based explanation systems are so simple, so easily implemented, that they encourage experimentation and, hence, the faster recognition of open research issues. Our belief is that exploring those further issues will be made easier by keys (and that is our current research direction). Time will tell if that belief is correct.
APPENDIX: RESEARCH DIRECTIONS

Looking though the above, we can see numerous possibilities for future work. Some issues relate directly to keys, while others relate more to issues with as human cognitive and, incremental knowledge acquisition.

RQ0) How to evaluate “explanation?” Many of the following will need a way to rank different explanation methods. Hence, our first research question is how to certify an explanation evaluation rig. If we say that a “useful” explanation means we know how to better build a model, then Figure 3 can be used for that ranking purpose. Specifically, explainer1 is better than explainer2 if more goals are achieved after making fewer decisions.

For that evaluation, there are several cases. Case1: If the y axis of Figure 3 comes from some model, then the y values can be scored via rerunning the model with new constraints learned from the explanation algorithm. Case2: If there is no model, and the y values from some historical record of a project, then that data should be divided using time stamps into before and after data. The after data could be sorted according to its overlap with the recommendations generated from explanations built from the before data. Explainer1 is better than explainer2 if the after data with highest overlap is somehow better (e.g. fewer software defects) than the rest.

RQ1) Can we build a keys detector? Research directions for such a detector including the following. Firstly, keys could be detected if, after applying feature and instance selection, the reduced data space generates models that perform as well as using all the data. For a discussion on this approach, see Papakoni, Peters et al. [36], [37].

Secondly, run some very simple and very fast data miners run over the data building models using N or 2N features. If any learner does no better than another, but using only half the features, then kill the larger learner and start a new learner that uses half the features of the smaller learner. Keys would be defected if the final N value is much smaller than the total number of features. For a discussion on this approach, see [38].

Thirdly, researchers could (a) take some well-explore SE domain; then (b) commission the prior state-of-the-art (SOTA) method known for that domain; then (c) compare results from (say) KEYS0 and the SOTA; then (d) declare that this domain has a keys effect if KEYS0 can control that domain using far fewer features than the SOTA. Note that, of the three approaches to RQ1 listed here, this third proposal would be the most labor intensive.

RQ2) What is the generality of keys effect? If we have an automatic method for determining if a data set is amenable to keys, then we need to run that detector on as many data sets as possible in order to learn the extent of the keys effect.

RQ3) Where do keys come from? Another way to assess the generality of the keys effect would be to understand what causes them. If we knew that, then we could apply the methods of this paper whenever we see those causative factors. In §V, it was speculated that power laws within programmer teams lead to keys. To test that theory we could (e.g.) built defect predictors from projects that evolved from small single person into large teams. If power laws cause keys, then we would predict that algorithms like KEYS0 would be less/more effective earlier/later in that project life cycle (respectively).

RQ4) How does keys compare to other explanation algorithms? §III and §IV depreciated standard explanation algorithms like FFTtrees [10], LIME [15], and SHAP [16] arguing that they could only handle single goals and (in the case of LIME and SHAP) only commented on the effects of single variables on the goal. It is hence appropriate to check what is lost if we move from multiple multiple variable multi-goal reasoning (with KEYS0) to single variable and single-goal reasoning (with the other approaches). If we re-run examples like §IV and the net gain with KEYS0 over these other algorithms is minimal, and those other approaches produced very small models, then that would challenge the motivation for this work.

RQ5) Can keys simplify prior results? In the above, we speculated that the incremental active learning work of Yu,Tu et al. [20], [21] could be simplified via keys. This conjecture needs to be checked.

Another example of prior work that might be helped by keys is incremental anomaly detection. Figure 5 proposed an incremental knowledge capture approach to system construction. In such an approach, it is useful to have anomaly detectors that understand when old ideas have become out-dated, or when new data is “out-of-scope” of the previously generated model. There are many ways to generate anomaly detectors [39] and we conjecture that a succinct keys-based summary of past data might make it easier to determine when new data is anomalous.

RQ6) What are the best algorithms for finding keys? The KEYS0 algorithm described above in §IV is very simple, possibly even simplistic. Hence, it is worthwhile consider different ways to code that algorithm.

The KEYS0 algorithm described above is a greedy search in that it prunes half the data at each level of its recursive search. Lustosa et al. [33] prefers instead a global analysis where the whole cluster tree is generated, after which time the algorithm hunts around all nodes looking for things to prune and things to keep. Greedy algorithms run faster but global algorithms use more information about the data. Which works best? Or is there some way to amalgamate the two approaches (e.g. some local search in the style of MaxWalkSat [40])?

Also, KEYS0 cluster the data via hierarchical random projects. There are so many other ways to cluster data (e.g. see https://scikit-learn.org/stable/modules/clustering.html) that it would be useful to explore other methods. For example if the data is particularly complex, is there any role for other algorithms such as a neural autoencoder? More generally, can we refactor the code in steps1,2,3,4,5 into some object-oriented design with abstract super-classes like “cluster” and concrete sub-classes for different (e.g.) clustering algorithms? Such a refactoring would turn the above code into a workbench within which multiple algorithms could be mixed and matched in an effort to find better explanation algorithms.

No matter how the clusters are generated, some report
must be made to the user about the different between the clusters (this different was reported in §IV as the constraints “cylinders ≤ 4” and “origin==”). KEYS0 uses a simple greedy frequency-based method (combine adjacent ranges that have similar best,rest frequencies; tank feature ranges, favoring those that are more frequent in best than rest; print the top-ranked range) and there are so many other feature and range ranking methods to try [41], [42].

For simple data sets like the auto93 data set explored in §IV only 2 constraints are generated before the algorithm cannot find anything else of interest. Lustosa et al. [33] reports studies in larger data sets (with 128 features) where his keys finder returns very many constraints. Is there an early stopping rule that can be applied to find enough useful constraints, but no more?

It is interesting to compare KEYS0 with genetic algorithms (GAs). GAs mutates a population of, say, 100 individuals across many generations. Each generation applies some select operator (to remove worse individuals) then combines the survivors to create the next generation. KEYS0, on the other hand, applies its select operator to a much larger initial population, after which it does no mutation (hence, no generation i + 1). Prior results by Chen et al. [43] suggested that this over-generate-population can do as well, or better, than multi-generation mutation (also, his approach is much faster than evolutionary methods). But evolutionary programming is a rapidly progressing field. Hence, it would be wise to recheck Chen’s conclusions against (e.g.) Hyperopt [44].

**RQ6) What is the impact of user mistakes?** One cognitive issue wit the current KEYS systems is that humans make many mistakes. What happens to Figure 1 if humans make a wrong decision along the y-axis? How do we detect that mistake? For example, would some unsupervised outlier detection [45] suffice? And how do we repair those mistakes (Yu et al. have some preliminary ideas on that [20]).

Another cognitive issue is that humans have different world views. Hence, reasoning about teams is very different to reasoning about one or two people. In the studies mentioned above regarding integration with human agency, Yú, Tu et al. worked mostly with one or two oracles [20]. [21]. How their methods scale to teams? Within the space of possible explanations, would we need to (e.g.) add in some multi-goal reasoning [46] so that we can appease the most number of competing goals as possible? On the other hand, rather than seek appeasement, it is better to report separate sets of conclusions where each set satisfies a different set of goals (e.g. see the Pareto clusters in Figure 5 of [47])?

**RQ7) Can visualizations replace rules?** One of the more interesting results of Lustosa et al. [33] is that large data spaces can be explored with reference to just a few ranges from a few features. Given that, can we offer users succinct visualizations of the data showing just the frequency counts of those ranges? And if users examined that space, would they find their own plans for controlling the data? And would those plans work better than the plans generate via pure algorithmic means by Lustosa et al. [33]?

**RQ8) How to maintain privacy and accountability?** In the above, it was proposed to cache the rig of Figure 1 then re-run it for accountability purposes. This raises two data management systems issues. Firstly, if we retain some or all the data of Figure 1 do we need some (e.g.) mutation policy to reduce the probability of identify disclosure within that data? [36]? Secondly, how much past data do we need to keep in order to support future accountability? If we must keep all the past data then that could become a significant data storage issue. On the other hand, recalling Steps 1,2,3,4,5, would it suffice to just keep the distant points $P_1, P_2$ found at each level of the recursion? Or is the best data retention policy somewhere in-between? (Aside: see Nair and Peters et al. [36], [48] for different proposals on selecting the most informative prior data).