Path-based SST relies on classical results from labelled combinatorial structures [11] to uniformly sample the set of program paths with length in $[1, T]$. Each path sample is provided to a constraint solver (oracle) and labelled as feasible or infeasible; see [9] and references therein. The infeasibility of a given path arises if it violates some dependencies between different parts of the program, referred to as *XOR patterns*. For instance if two `if` nodes are based on an unchanged expression, then their successors are correlated in every feasible path (if the program path includes the `then` successor of the first `if` node, it must also include the `then` successor of the second `if` node).

Because of the small number of available labelled paths (due to the labelling cost) compared to the complexity of the "natural" search space, i.e. that of long strings on a large alphabet, a frugal propositional representation inspired by Parikh maps [12] is considered. For $t = 1 \ldots T$, let $s[t]$ denote the t-th symbol in string s, set to value v_f if the length of s is less than t.

- To each symbol v, is associated an integer attribute a_v; $a_v(s)$ is the number of occurrences of symbol v in path s.
- To the i-th occurrence of a symbol v, is associated a categorical attribute $a_{v,i}$. Attribute $a_{v,i}(s)$ gives the next informative[1] symbol following the i-th occurrence of symbol v in s (or v_f if s contains less than i occurrences of v).

Preliminary attempts at discriminant learning have been hindered by the tiny percentage of the feasible paths, as could have been expected from [8]. A generative learning approach was then considered.

3 Overview of *EXIST*

This section describes a sampling algorithm called *EXIST* for *Exploration vs eXploitation Inference for Software Testing*, able to retrieve distinct feasible paths with high probability based on a set $\mathcal{E}$ of feasible/infeasible paths. $\mathcal{E}$, initially set to a small set of labelled paths, is gradually enriched with the paths generated by *EXIST* and labelled by the constraint solver.

EXIST proceeds by iteratively exploiting and updating a probabilistic model $\mathcal{P}$. *EXIST* involves two modules: the *Init* module estimates the probability for a path to be feasible conditionally to its extended Parikh description[2]; the *Decision* module uses the $\mathcal{P}$ model to iteratively construct the current path s.

3.1 *Decision* module

Let s (resp. v) denote the path under construction (resp. the last node symbol in s). Let i be the total number of occurrences of v in s. Let w be one possible successor node of v; if w is selected, the total number of w symbols in the final path will be at least the current number of occurrences of w in s, plus one; let j_w denote this number.

Let us define $p_s(w)$ as the probability for a path S to be feasible conditionally to $F_{s,w}(S) = [a_{v,i}(S) = w] \wedge [a_w(S) \geq j_w]$, estimated by the *Init* module; $p_s(w)$ is conventionally set to 1 if there is no path in $\mathcal{E}$ satisfying $F_{s,w}$.

Probabilities $p_s(w)$ for w ranging over the successors of v are used to select the next node in s. Three options have been considered in order to favor the generation of a new feasible path.
The *Greedy* option selects the successor node w maximising $p_s(w)$.
The *RouletteWheel* option stochastically selects node w with probability proportional to $p(s, w)$.
The *BandiST* option considers the multi-armed bandit problem where every bandit arm corresponds to a successor w of the current node v and the associated reward is $p_s(w)$, and uses the UCB1 algorithm [1] for determining the best arm/successor node.

3.2 *Init* module

The *Init* module determines how the conditional probabilities used by the *Decision* module are estimated. The baseline *Init* option computes $p_s(w)$ as the fraction of paths in $\mathcal{E}$ satisfying $F_{s,w}$ that are feasible. However, this option fails to guide *EXIST* efficiently due to the disjunctive nature of the target concept, as shown on the following toy problem.

[1] Formally, $a_{v,i}(s)$ is set to $s[t(i) + b]$, where $t(i)$ is the index of the i-th occurrence of symbol v in s; b is initially set to 1; in case $a_{v,i}$ takes on a constant value over all examples, b is incremented.

[2] This probabilistic model space is meant to avoid the limitations of probabilistic FSAs and Variable Order Markov Models [4]. On one hand, probabilistic FSAs (and likewise simple Markov models) cannot model the long range dependencies of the *XOR patterns*. On the other hand, although Variable Order Markov Models can accommodate such dependencies, they are ill-suited to the sparsity of the initial data available.