Introduction to Program Synthesis (WS 2024/25) Chapter 3.1 - Traditional Methodologies (Naive Search)

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Naive Search

- Naive search methods → Easy to implement
 - ► Lack of sophisticated search strategies
- ▶ Use of such methods is usually entails a high computational effort
- Can be applied to a wide range of search problems
 - ▶ Program synthesis can be considered a search problem
 - Search problems can be considered decision problems

Naive Search

- Naive search → Commonly performed in enumerative or stochastic fashion
 - ▶ Have been successfully applied to many problems in the past
- **► Exhaustive Search** → Enumerative search problem
 - Iterative or recursive search method
 - Prone to combinatorial explosion
- ► Monte-Carlo Search → Stochastic search problem
 - ► Search is based on random sampling
 - ▶ Pure random search → divergent method without any guarantee of convergence or success

Naive Search

candidate— potential solution that can replace the current (best) solutionconfiguration— setting of a candidatesolution— valid and complete solution that satisfies all constraintspartial solution— incomplete solution that does not fulfill all constraintsfeasible solution— complete or partial solution that adheres all constraintsoptimal solution— best (ideal) possible solutiondead end— point where further extension would cause violating constraintsbacktrack— return to a previous decision pointsearch space— space of all possible permutations and choices

Table: Basic terminologies used for the description of search problems and algorithms

Naive Search

- ► Characteristics of a search problem:
 - ▶ Set of states $S_1, S_2, ..., S_N \rightarrow \text{State space}$
 - Start state $S_0 \rightarrow$ State after initialization
 - ▶ Goal state S_G → Ideal solution
 - Successor function $\delta \to \text{Transition operator}$

Naive Search

Definition (Search Problem)

Given a set X of candidate solutions, and a property $P: X \to \{\text{True}, \text{False}\}$, find a $x \in X$ such that P(x) is True.

Enumerative Search: Considerations

- No efficient solution method exists → Exhaustive Search
- ▶ Evaluation of each possibility in sequential fashion
 - Also known as brute force search (BFS)
- BFS has two operations that are performed with a search problem
 P and candidate c
 - ightharpoonup valid $(\mathcal{P},c) o \mathsf{Checks}$ the validity of candidate solutions
 - output $(\mathcal{P}, c) \rightarrow \text{Outputs}$ the optimal solution
 - lacktriangledown first $(\mathcal{P})
 ightarrow \mathsf{Returns}$ the first element for the iteration
 - lacktriangleright next (\mathcal{P}) ightarrow Returns the next element considered in the iteration
 - ▶ terminate (P, c, n) → Checks terminate conditions

Enumerative Search: Characteristics

Algorithm Brute Force Search

```
1: c \leftarrow \operatorname{first}(\mathcal{P})

2: n \leftarrow 0

3: repeat

4: if \operatorname{valid}(\mathcal{P}, c) then \operatorname{output}(\mathsf{P}, c)

5: end if

6: c \leftarrow \operatorname{next}(\mathcal{P})

7: n \leftarrow n + 1

8: until \operatorname{terminate}(\mathcal{P}, c, n) == \operatorname{true}
```

▶ Until termination criteria not triggered

Enumerative Search: Historical Example

- **► Enigma machine** → cipher device
 - Developed and used in the early mid 20th century
 - Encrypted military, diplomatic and commercial communication
 - Widely used by the Nazis in the second world war
- ▶ Encryption via rotors that manipulate electric pathways
 - Additional plugboard for letter swapping
 - ▶ Increases cryptographic strength



Figure: Enigma cipher machine (Source: Wikimedia)

Enumerative Search: Historical Example

- ightharpoonup Turing bomb ightarrow Machine that is able to break the Enigma
 - Developed by Alan Turing during WWII
 - ▶ Relies on electric-mechanical exhaustive search
- Successfully decrypted intercepted German radio messages
 - ▶ Exhaustive search in the *setting space* of the Enigma
 - ▶ Enigma used in WWII had 158, 962, 555, 217, 826, 360, 000 $\approx 10^{20}$ different settings



Figure: Turing bomb at Bletchley Park in times of WWII (UK) (Source: Wikimedia)

AIM: Introduction to Program Synthesis

Recursive Enumeration

Definition (Enumerative Problem)

A enumeration problem \mathcal{P} is characterized with:

- An arbitrary alphabet Σ
- ▶ A relation over strings or symbols \mathcal{R} : $\mathcal{R} \subseteq \Sigma^* \times \Sigma^*$

An enumerative search algorithm V produces a sequence y for the input x given to V without duplicates and for $z \in y \iff (x, z) \in \mathcal{R}$.

Recursive Enumeration

Listing: Sub-sequences of 1 .. 4 in military order

Listing: Sub-sequences of 1 .. 4 in lexicographic order

```
1 2 3 4 1 2 4 1 3 4 1 4 2 2 3 2 3 4 2 4 3 3 4
```

- ightharpoonup The number of subsequences of 1 .. n grows exponentially with n
 - ▶ Doubles when *n* is incremented by 1

Enumerative Search: Recursive Enumeration

- ightharpoonup Traditional exhaustive search ightharpoonup executed in iterative fashion
- ightharpoonup Recursive search ightharpoonup Enumerative search performed with recursion
 - Base case is defined as goal state or dead end
 - Preferred for enumerative search problems solved with (data) structures well suited for recursion → Tree, Graph, ...

Recursion

Advantages:

- ► Allows problems to be solved in a concise and straight-forward way
- ▶ More readable code that is easier to understand
- ▶ Less time needed to implement solvers for certain problems
- Dynamic properties

▶ Disadvantages:

- Mostly more time and space requirements
- \blacktriangleright Overhead caused by a high number of function calls \rightarrow can be optimized with **tail recursion**

Enumerative Search: Recursive Enumeration

```
Algorithm Enumerative Recursive Search (ERS)
    Arguments
    S_n: Starting or intermediate state
    Return
    S_{\sigma}: Goal or base case
 1: procedure ERS(S_n)
        if S_n == G then
                                          ▶ Base case 1: Intermediate state is goal state G
 3:
            output S_n
 4.
           return Sn
 5:
        else if S_n == null then
                                          ▶ Base case 2: Intermediate state does not exist
 6:
            return S<sub>n</sub>
       else
            S_{n+1} \leftarrow \delta(S_n)
                                      ▷ Execute transition function to obtain next element
           ERS(S_{n+1})
 9:
                                                                  ▶ Perform recursion step
10:
        end if
11: end procedure
```

Enumerative Search: Backtracking

- ▶ **Backtracking** → Stepping back to a prior decision point
 - ► Making use of recursion to explore all valid possibilities
- ightharpoonup Recursive function ightharpoonup Calls itself until base case is reached
- ► Backtracking rejects candidates that cannot fulfill the conditions required for the solution
 - ightharpoonup Extension of recursion by using a acceptance function α
 - ▶ Let S be a state then α is defined as $\alpha : S \rightarrow \{\text{True, False}\}$

Traditional MethodologiesEnumerative Search: Historical Example

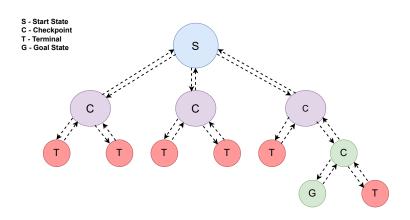


Figure: Backtracking

Exhaustive Search

13:

14.

end if

15: end procedure

Algorithm Enumerative Recursive Search (ERS) with backtracking Arguments S_n : Starting or intermediate state Return S_{g} : Goal or base case 1: procedure $ERS(S_n)$ if $S_n == G$ then ▶ Base case 1: Intermediate state is goal state G 3: output S_n 4. return S. else if $S_n ==$ null then 5. ▶ Base case 2: Intermediate state does not exist. 6: return S_n else $S_{n+1} \leftarrow \delta(S_n)$ 8. if $\alpha(S_{n+1}) ==$ true then ▶ Backtracking: Call of rejection function $ERS(S_{n+1})$ 10: ▶ Recursive step if solution is accepted 11. else 12. return S_n ▶ Return checkpoint state in case of rejection end if

Monte-Carlo Search

- ► Monte-Carlo Search (MCS) → Based on Monte-Carlo Sampling
 - ► Also known as random search or Monte-Carlo method
- Foundation of randomized search heuristics
 - ► Family of black-box optimization and search algorithms
 - ▶ Local search methods, evolutionary algorithms, ...

Randomized Search

- ► Randomized search methods → Commonly performed iteratively
- ▶ New samples are drawn from a predefined probability distribution
 - ▶ Uniform and normal distribution are common choices
 - ▶ Either one new search point or a set of points are sampled
 - ▶ Evaluation with a cost function i.e. $\mathcal{C}: \mathbb{R}^n \to \mathbb{R}$
 - lacktriangleright Termination criterion ightarrow number of iterations or ideal cost function value
 - ► Popular representatives:
 - Random walk
 - ► Hill climbing

Randomized Search: Random Walk

Algorithm Random Walk (RW)	
1: <i>P</i> ∼ <i>U</i>	▷ Sample initial state
2: repeat	▶ Until termination criteria not triggered
3: $Q \sim U$ 4: $P \leftarrow Q$	> Sample new search point
4: $P \leftarrow Q$	▶ Replace old search point
5: until \mathcal{P} meets termination criterion	
6: return \mathcal{P}	▶

- ▶ Divergent and unbounded/unrestricted stochastic process
- ▶ Based on pure random sampling
- lacktriangle No rejection criterion ightarrow acceptance of inferior steps

Randomized Search: Random Local Search

- ► Random Local Search (RLS) → Exploits the neighbourhood of a search point by chance
- \blacktriangleright A neighbourhood is sampled in each step \to Neighbourhood function ${\mathcal N}$
- ► A strategy is applied to accept or reject members of the neighbourhood
- lacktriangledown Popular method in the family of RLS algorithms ightarrow Hill climbing

Randomized Search: Hill Climbing (HC)

Randomized Search: Random Local Search

- ► **Stochastic HC** → Selection among improving (uphill) neighbours
- ► First-choice HC → Sampling of successors until one is better
- ► Random restart HC → Re-initialize the search state by chance i.e. after a budget of steps has been exceeded
- ► Evolutionary-based HC → Performs mutations by chance on the respective problem representation and selects improving variations

Randomized Search: Hill climbing

- ▶ RLS requires the existence of a neighbourhood property
- ▶ Success strongly depended on the size of the solution space
 - ▶ If the percentage *s* of solutions in the search space is known, the success probability after performing *n* trials can be calculated with counterprobability
 - $s = 3, n = 50 \rightarrow 1 0.97^{50} \approx 0.78 = 78\%$
- ► Success of RLS methods depends on the shape of the state-space landscape