# Informed search algorithms Michal Pěchouček, Milan Rollo 

Department of Cybernetics<br>Czech Technical University in Prague


http://cw.felk.cvut.cz/doku.php/courses/ae3b33kui/start

## Recommended literature

:: Artificial Intelligence: A Modern Approach (Third Edition) by Stuart Russell and Peter Norvig, 2007 Prentice Hall.

http://aima.cs.berkeley.edu/

## Informed state space search strategies

:: implement efficient ways to find an optimal solution and during that process they utilize qualitative information about various states of the state space.

During the search we use (at least one):

- specific information about a cost of given state in state space
- specific information about a cost of applying each possible action
- heuristic information, estimation suitability of use of given action with respect to the state space search efficiency
$::$ This information is used for the design of heuristic algorithm (called also as Best-First-Search), which selects a node for expansion. Such a node leads the search process to an optimal solution. When well-designed heuristic algorithm minimizes the search of those parts of state space that don't lead to optimal solution.


## Informed state space search strategies



## Best-first search

Design of the best-first search algorithm builds on a classic algorithm for uninformed state space search:

1. begin
2. open $:=$ [Start], closed := []
3. while (open <> []) do begin

X := FIRST(open)
closed := closed + [X], open := open - [X]
if $\mathrm{X}=\mathrm{GOAL}$ then return(SUCCESS)
else begin
8.
9.
10.
11.
$\mathrm{E}:=\operatorname{expand}(\mathrm{X})$
E := E - closed
open := open +E
end
12.
end
13. return(failure)
14. end.

## Best-first search

only the selection of first element in a list is replaced by the selection of the best element

1. begin
2. open := [Start], closed := []
3. while (open <> []) do begin
$\mathrm{X}:=$ BEST (open)
closed := closed + [X], open := open - [X]
if $\mathrm{X}=\mathrm{GOAL}$ then return(SUCCESS)
else begin
E := expand (X)
E := E - closed
open := open + E
end
4. 
5. end
6. return(failure)
7. end.

## Evaluation function

:: When algorithm tries to select a best state to expand (e.g. $s_{n}$ ) from current state (e.g.. $s_{m}$ ) it works with following functions:

- $c(m, n)$ - cost of action we need to apply to get from state $m$ to state $n$
- $g(m)$ - overall cost, sum of costs of all actions that were applied from the initial state to state m
- $h(n)$ - real or estimated total cost, sum of costs of all actions we need to apply from state $n$ to the goal state.
:: it is thus necessary to propose an evaluation function $f$, that will integrate functions $c, g$ and $h$ in a sophisticated way and will ensure a reasonable behavior in a given domain.


## Examples of evaluation function

- Gradient search (hill-climbing search)- where $\forall m, n: f(m, n)=c(m, n)$
- easy to implement, fast, resistive to infinite loops - but often gets stuck at a local optimum !!!


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- minimizes number of steps (depth) to the solution


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- minimizes number of steps (depth) to the solution
- Greedy search algorithm - $\forall m, n: f(m, n)=h(n)$ if there is an edge from $m$ to $n$. Here the $h(n)$ is heuristic estimation of path cost from node $n$ to closest goal node
- non-optimal, incomplete


## Greedy search



Straight-line distance to Bucharest
Arad 366
Bucharest 0
Craiova 160
Dobreta 242
Eforie 161
Fagaras 178
Giurgiu 77
Hirsova 151
Iasi 226
Lugoj 244
Mehadia 241
Neamt 234
Oradea 380
Pitesti 98
Rimnicu Vilcea 193
Sibiu 253
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Urziceni 80
Vaslui 199
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## Greedy search

 $\square \square \square \square \square \square \square \square \square \square \square \square \square \square \square \square \square$

- $A^{*}$ algorithm uses the best-first search approach, where each state has assigned an evaluation function:
$-f(n)=g(n)+h(n)$
- remark: $(c, g$ a $h)$ in a form $f(n, m)=c(m, n)+g(m)+h(n)$ could be written as $f(n)=g(n)+h(n)$ because $g(n)=g(m)+c(m, n)$, where argument $m$ does no longer influence the value of the function.
- To set evaluation function $f$ in a form $f(n)=g(n)+h(n)$ is a nontrivial problem because of the function $h(n)$ whose value is not known a priori and we have to estimate it.
- Due to the fact, that we optimize the behavior of algorithm, we want this estimation to be as precise as possible - we want the value of $h(n)$ to be as close to the value of $h^{*}(n)$ (real value). Function $h(n)$ is called heuristic function.
- Evaluation function $f(n)$ is thus an estimation of real values, that we will get by function $f^{*}(n)=g^{*}(n)+h^{*}(n)$ where $g(n)=g^{*}(n)$ (in most cases)


## Admissibility of $A^{*}$ algorithm

- Which features must the heuristic function $h(n)$ have? What will happen if $h(n)>h^{*}(n)$ ? And what if $h(n)<h^{*}(n)$ ?


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- For an algorithm to behave in a reasonable manner, i.e to find an optimal solution first, it must hold that:

$$
\forall n: 0 \leq h(n) \leq h^{*}(n)
$$

- When that holds, we say that heuristic function is admissible.
- $A^{*}$ algorithm uses best-first search approach where each state is evaluated by function $f(n)=$ $g(n)+h(n)$, where $h(n)$ is
- $A^{*}$ algorithm will always find an optimal solution.
is BFS optimal?


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- $A^{*}$ algorithm will always find an optimal solution.
is BFS optimal?
yes, because for BFS $f(n)=g(n)+h(n)=g(n)$. Thus $0=h(n)<h^{*}(n)$ and heuristic is admissible.


## Example of heuristic for path search



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## Example of heuristic for path search



1. begin
2. open := [Start], closed := []
3. 
4. 
5. 
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7. 
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13. return(failure)
14. end.

## Additional properties of $\mathrm{A}^{*}$

clarification of operations in $A^{*}$ at line 9-10:

- in case that node $e \in \mathrm{E}$ is already in an open list
- with value $f(e)$ better, than the node is not added into the open list at line 10
- with value $f(e)$ worse, than the better node is added into the open list at line 10 and the worst node is removed
- in case that node $e \in \mathrm{E}$ is already in a closed list
- with value $f(e)$ better, than that node is removed from the E list at line 9
- with value $f(e)$ worse, than that node is not removed from E list at line 9 , it is removed from the closed list.


## Heuristic monotonicity

Heuristic function is monotone/consistent (localy admissible) if
i. $\forall n_{1}, n_{2}$, where $n_{1}$ expands into $n_{2}: h\left(n_{1}\right)-h\left(n_{2}\right) \leq \operatorname{cost}\left(n_{1}, n_{2}\right)$, where $c\left(n_{1}, n_{2}\right)$ is real cost from $n_{1}$ to $n_{2}$
ii. $h($ goal $)=0$.
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ii. $h($ goal $)=0$.
each monotone heuristic function is admissible.
Proof:
for $n_{0} \rightarrow n_{1} \ldots \quad h\left(n_{0}\right)-h\left(n_{1}\right) \leq c\left(n_{0}, n_{1}\right)$ due to the monotonicity
for $n_{1} \rightarrow n_{2} \ldots h\left(n_{1}\right)-h\left(n_{2}\right) \leq c\left(n_{1}, n_{2}\right)$ due to the monotonicity
for $n_{k-1} \rightarrow$ goal $\ldots h\left(n_{k-1}\right)-h($ goal $) \leq c\left(n_{k-1}\right.$, goal $)$
if $h($ goal $)=0$ then when we sum all lines $h\left(n_{0}\right) \leq c\left(n_{0}\right.$, goal $)$

## Dominance

- Having two admissible heuristics $h_{1}$ and $h_{2}$ so that $\forall n: h_{1}(n) \leq h_{2}(n)$, then we say that heuristic $h_{2}$ dominates $h_{1}$.
- Both heuristics will find optimal solution, but $h_{2}$ needs to expand less nodes than $h_{1}$.
- We have to take care that the computational time of dominating heuristic will not last considerably longer than search of larger portion of state space.


Start State


Goal State

| 2 | 8 | 3 |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 6 | 4 | 5 | 6 | 0 |  |  |  |
|  | 7 | 5 |  |  |  |  |  |  |
| 2 | 8 | 3 |  |  |  | 1 | 2 | 3 |
| 1 |  | 4 | 3 | 4 | 0 | 8 |  | 4 |
| 7 | 6 | 5 |  |  |  | 7 | 6 | 5 |
|  |  |  |  |  |  | Goal |  |  |
| 2 | 8 | 3 | 5 | 6 | $0$ |  |  |  |
| 1 | 6 | 4 |  |  |  |  |  |  |
| 7 | 5 |  |  |  |  |  |  |  |
|  |  |  | Titles out of place | Sum of distances out of place | 2 x the number of direct tile reversals |  |  |  |

## Comparison of heuristics

Effective Branching Factor: average number of children $b^{*}$ of each node. For depth $d$ and total number of expanded nodes $N$ then must hold $N=1+b^{*}+\left(b^{*}\right)^{2}+\cdots+\left(b^{*}\right)^{d}$

|  | Search Cost |  |  | Effective Branching Factor |  |  |
| ---: | ---: | ---: | ---: | :---: | :---: | :---: |
| $d$ | IDS | $\mathrm{A}^{*}\left(h_{1}\right)$ | $\mathrm{A}^{*}\left(h_{2}\right)$ | IDS | $\mathrm{A}^{*}\left(h_{1}\right)$ | $\mathrm{A}^{*}\left(h_{2}\right)$ |
| 2 | 10 | 6 | 6 | 2.45 | 1.79 | 1.79 |
| 4 | 112 | 13 | 12 | 2.87 | 1.48 | 1.45 |
| 6 | 680 | 20 | 18 | 2.73 | 1.34 | 1.30 |
| 8 | 6384 | 39 | 25 | 2.80 | 1.33 | 1.24 |
| 10 | 47127 | 93 | 39 | 2.79 | 1.38 | 1.22 |
| 12 | 364404 | 227 | 73 | 2.78 | 1.42 | 1.24 |
| 14 | 3473941 | 539 | 113 | 2.83 | 1.44 | 1.23 |
| 16 | - | 1301 | 211 | - | 1.45 | 1.25 |
| 18 | - | 3056 | 363 | - | 1.46 | 1.26 |
| 20 | - | 7276 | 676 | - | 1.47 | 1.27 |
| 22 | - | 18094 | 1219 | - | 1.48 | 1.28 |
| 24 | - | 39135 | 1641 | - | 1.48 | 1.26 |

## Optimal efficiency of $A^{*}$

:: We say that $A^{*}$ is optimally efficient. It means that for any heuristic function there isn't any other optimal algorithm that will expand less nodes than $A^{*}$.

We know about $A^{*}$ that algorithms is optimal, complete and optimally efficient. But it still doesn't mean that it is suitable for all search problems. Unfortunatally the memory comsumption still grows exponentially (it was prooved that this holds in cases when $\left|h(n)-h^{*}(n)\right|>$ $\left.O\left(\log h^{*}(n)\right)\right)$.
:: Time complexity is not the major problem of $A^{*}$. Due to the fact that $A^{*}$ must keep all expanded states in a memory, it often happens that we run out of the memory sooner than we run out of time.


## Variants of algorithms improving memory usage

- IDA* - iterative deepening $A^{*}$ algorithm: Works in a same way as an iterative-deepening depth-first search (IDDFS), with that difference that we don't increase the depth limit, but the least value of $f$ which is higher than $f$ from previous run.
- RBFS - Recursive best first search, recursive IDA*. It limits the value of $f$ to the second best in given layer.


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IDA* and RFBS are optimal (i.e., they cannot miss the best solution), MA* and SMA* can miss optimum and get stuck in a local extreme (when the open list size bound is small).

