CSP Introduction

CPSC 322 - CSPs 1

Textbook §4.0 - 4.2

Recap

- Recap
- 2 Dynamic Programming

Dynamic Programming

- 3 Variables
- 4 Constraints
- CSPs

Branch-and-Bound Search Algorithm

- Follow exactly the same search path as depth-first search
 - treat the frontier as a stack: expand the most-recently added node first
 - the order in which neighbors are expanded can be governed by some arbitrary node-ordering heuristic
- Keep track of a lower bound and upper bound on solution cost at each node
 - lower bound: LB(n) = cost(n) + h(n)
 - upper bound: UB = cost(n'), where n' is the best solution found so far.
 - if no solution has been found yet, set the upper bound to ∞ .
- When a node n is selected for expansion:
 - if $LB(n) \ge UB$, remove n from frontier without expanding it
 - this is called "pruning the search tree" (really!)
 - \bullet else expand n, adding all of its neighbours to the frontier



Branch and Bound Example

- http://aispace.org/search/
- Example: Load from URL http://cs.ubc.ca/~kevinlb/ teaching/cs322/BnBSearchDemo.xml

Variables

Strategy	Frontier Selection	Complete?	Space
Depth-first	Last node added	No	Linear
Breadth-first	First node added	Yes	Exp
A^*	Minimal $f(n)$	Yes	Exp
Branch-and-Bound	Last node added, with pruning	No	Linear

Recap

What can we prune besides nodes that are ruled out by our heuristic?

- Cycles
 - this one is really easy
- Multiple paths to the same node
 - if we want to maintain optimality, either keep the shortest path, or ensure that we always find the shortest path first

Recap

The main problem with A^* is that it uses exponential space. Branch and bound was one way around this problem.

Two others are:

- Iterative deepening
- Memory-bounded A*

Other search paradigms:

- Backwards search
- bi-directional search



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Dynamic Programming

Idea: for statically stored graphs, build a table of dist(n) the actual distance of the shortest path from node n to a goal.

Initialize $dist(n) = \infty$ for each node n

Then repeatedly, until no dist(n) value changes, set each dist(n) value to the smallest (neighboring dist(n') value + cost of reaching n' from n):

$$dist(n) = \left\{ \begin{array}{ll} 0 & \text{if } is_goal(n), \\ \min_{\langle n,m\rangle \in A}(|\langle n,m\rangle| + dist(m)) & \text{otherwise}. \end{array} \right.$$

Dynamic Programming

There are two main problems:

- You need enough space to store the graph.
- The dist function needs to be recomputed for each goal.

Complexity: polynomial in the size of the graph.

- but so is DFS (in fact, it's linear)
- the gain is when there are lots of nested cycles

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Variables

- Recall that we defined the state of the world as an assignment of values to a set of (one or more) variables
 - variable: a synonym for feature
 - we denote variables using capital letters
 - each variable V has a domain dom(V) of possible values
- Variables can be of several main kinds:
 - Boolean: |dom(V)| = 2
 - Finite: the domain contains a finite number of values
 - Infinite but Discrete: the domain is countably infinite
 - Continuous: e.g., real numbers between 0 and 1
- We'll call the set of states that are induced by a set of variables the set of possible worlds

Crossword Puzzle:

- variables are words that have to be filled in
- domains are English words of the correct length
- possible worlds: all ways of assigning words

CSPs

Crossword Puzzle:

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Crossword 2:

- variables are cells (individual squares)
- domains are letters of the alphabet
- possible worlds: all ways of assigning letters to cells

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- variables are cells (individual squares)
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Sudoku

- · variables are cells
- domains are numbers between 1 and 9
- possible worlds: all ways of assigning numbers to cells

More Examples

Scheduling Problem:

- variables are different tasks that need to be scheduled (e.g., course in a university; job in a machine shop)
- domains are the different combinations of times and locations for each task (e.g., time/room for course; time/machine for job)
- possible worlds: time/location assignments for each task



More Examples

Scheduling Problem:

- variables are different tasks that need to be scheduled (e.g., course in a university; job in a machine shop)
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- possible worlds: time/location assignments for each task

• n-Queens problem

- variable: location of a queen on a chess board
 - ullet there are n of them in total, hence the name
- domains: grid coordinates
- possible worlds: locations of all queens



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Constraints

Constraints are restrictions on the values that one or more variables can take

- Unary constraint: restriction involving a single variable
 - of course, we could also achieve the same thing by using a smaller domain in the first place
- k-ary constraint: restriction involving the domains of k different variables
 - it turns out that *k*-ary constraints can always be represented as binary constraints, so we'll often talk about this case
- Constraints can be specified by
 - giving a list of valid domain values for each variable participating in the constraint
 - giving a function that returns true when given values for each variable which satisfy the constraint
- A possible world satisfies a set of constraints if the set of variables involved in each constraint take values that are consistent with that constraint

Crossword Puzzle:

- variables are words that have to be filled in
- domains are valid English words
- constraints: words have the same letters at points where they intersect

Crossword 2:

- variables are cells (individual squares)
- domains are letters of the alphabet
- constraints: sequences of letters form valid English words

Sudoku

- variables are cells
- domains are numbers between 1 and 9
- constraints: rows, columns, boxes contain all different numbers



More Examples

Scheduling Problem:

- variables are different tasks that need to be scheduled (e.g., course in a university; job in a machine shop)
- domains are the different combinations of times and locations for each task (e.g., time/room for course; time/machine for job)
- constraints: tasks can't be scheduled in the same location at the same time; certain tasks can't be scheduled in different locations at the same time; some tasks must come earlier than others; etc.

• n-Queens problem

- variable: location of a queen on a chess board
- domains: grid coordinates
- constraints: no queen can attack another



Dynamic Programming

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Constraint Satisfaction Problems: Definition

Definition

A constraint satisfaction problem consists of:

- a set of variables
- a domain for each variable
- a set of constraints

Definition

A model of a CSP is an assignment of values to variables that satisfies all of the constraints.



CSPs

Constraint Satisfaction Problems: Variants

We may want to solve the following problems with a CSP:

- determine whether or not a model exists
- find a model
- find all of the models
- count the number of models
- find the best model, given some measure of model quality
 - this is now an optimization problem
- determine whether some property of the variables holds in all models

CSPs: Game Plan

It turns out that even the simplest problem of determining whether or not a model exists in a general CSP with finite domains is $\mathcal{N}\mathcal{P}\text{-hard}$

we can't hope to find an efficient algorithm.

However, we can try to:

- find algorithms that are fast on "typical" cases
- identify special cases for which algorithms are efficient (polynomial)
- find approximation algorithms that can find good solutions quickly, even they may offer no theoretical guarantees
- develop parallel or distributed algorithms so that additional hardware can be used

