Lecture 7: Constraint satisfaction
Linear and integer programming

- Constraint satisfaction
  - Global constraints
  - Local search
  - Tools for SAT and CSP
- Linear and integer programming
  - Introduction

Global Constraints

- Constraint programming systems often offer constraints with special purpose constraint propagation (filtering) algorithms. Such a constraint can typically be seen as an encapsulation of a set of simpler constraints and is called a global constraint.
- A representative example is the alldiff constraint:

$$\text{alldiff}(x_1,\dots,x_n) = \{(d_1,\dots,d_n) \mid d_i \neq d_j, \text{for } i \neq j\}$$

  Example. A tuple (a,b,c) satisfies $\text{alldiff}(x_1,x_2,x_3)$ but (a,b,a) does not.
- $\text{alldiff}(x_1,\dots,x_n)$ can be seen as an encapsulation of a set of binary constraints $x_i \neq x_j$, $1 \leq i < j \leq n$.

Global Constraints: alldiff

- Global constraints enable compact encodings of problems.
- **Example.** N Queens
  Problem: Place n queens on a $n \times n$ chess board so that they do not attack each other.
  - Variables: $x_1,\dots,x_n$ (x_i gives the position of the queen on ith column)
  - Domains: [1..n]
  - Constraints: for $i \in [1..n-1]$ and $j \in [i+1..n]$:
    (i) $\text{alldiff}(x_1,\dots,x_n)$ (rows)
    (ii) $x_i - x_j \neq i - j$ (SW-NE diagonals)
    (iii) $x_i - x_j \neq j - i$ (NW-SE diagonals)

Global Constraints: Propagation

- In addition to compactness global constraints often provide more powerful propagation than the same condition expressed as the set of corresponding simpler constraints.
- Consider the case of alldiff:
  For $\text{alldiff}(x_1,\dots,x_n)$ there is an efficient hyper-arc consistency algorithm which allows more powerful propagation than hyper-arc consistency for the set of corresponding "$\neq$" constraints.
- **Example.**
  - Consider variables x_1,x_2,x_3 with domains $D_1 = \{a,b,c\}, D_2 = \{a,b\}, D_3 = \{a,b\}$.
  - Now $\text{alldiff}(x_1,x_2,x_3)$ is not hyper-arc consistent and the projection rule removes values a,b from the domain of x_1.
  - However, the corresponding set of constraints $x_1 \neq x_2, x_1 \neq x_3, x_2 \neq x_3$ is hyper-arc consistent and the projection rule is not able to remove any values.

Global Constraints: Other Examples

- When solving a CSP problem often a special purpose (global) constraint and an efficient propagation algorithm for it needs to be developed to make the solution technique more efficient.
- There is a wide range of such global constraints (see for example Global Constraint Catalog `http://www.emn.fr/x-info/sdemasse/gccat/`):
  - cumulative
  - diff-n
  - cycle
  - sort
  - alldifferent and permutation
  - symmetric alldifferent
  - global cardinality (with cost)
  - sequence
  - minimum global distance
  - k-diff
  - number of distinct values

  ...

CSP: Local Search

- GSAT and WalkSAT type of local search algorithms (see Lecture 4) can be generalized to CSPs.
- As an example we consider Min Conflict Heuristic (MCH) algorithm (Minton et al, 1990):
  Given a CSP instance P
  - Initialize each variable by selecting a value uniformly at random from its domain.
  - In each local step select a variable x_i uniformly at random from from the conflict set, which is the set of variables appearing in a constraint that is unsatisfied under the current assignment.
  - A new value v for x_i is selected from the domain of x_i such that by assigning v to x_i the number of conflicting constraints is minimized.
  - If there is more than one value with that property, one of the minimizing values is chosen uniformly at random.

MCH—cont'd

- One can add to MCH a random walk step like in NoisyGSAT (WMCH algorithm; Wallace and Freuder, 1995).
- MCH can be extended with a tabu search mechanism (Steinmann et al. 1997):
  - After each search step where the value of a variable x_i has changed from v to v', the variable-value pair (x_i, v) is declared tabu for the next tt steps.
  - While (x_i, v) is tabu, value v is excluded from the selection of values for x_i except if assigning v to x_i leads to an improvement in the evaluation function over the incumbent assignment.

CSP: Tabu Search

- A tabu search algorithm by Galiner and Hao is one of the best performing general local search algorithms for CSPs.
- TS-GH algorithm (Galiner and Hao, 1997):
  - Initialize each variable by selecting a value uniformly at random from its domain.
  - In each local step: among all variable-value pairs (x, v) such that x appears in a constraint that is unsatisfied under the current assignment and v is in the domain of x, select a pair (x, v) that leads to a maximal decrease in the number of violated constraints.
  - If there are multiple such pairs, one of them is chosen uniformly at random.
  - After changing the assignment of x from v to v', the pair (x, v) is declared tabu for tt steps (except when leading to an improvement).
- For competitive performance, the evaluation function for variable-value pairs needs to be implemented using caching and incremental updating techniques.

SAT: Local Search

- Local search methods have difficulties with structured problem instances.
- For good performance parameter tuning is essential. (For example in WalkSAT: the noise parameter p and the max_flips parameter.)
- Finding good parameter values is a non-trivial problem which typically requires substantial experimentation and experience.
- WalkSAT revised: adding greediness and adaptivity $\Longrightarrow$ Novelty+ and AdaptiveNovelty+ algorithms

WalkSAT

function WalkSAT(F,p):
  $t \leftarrow$ initial truth assignment;
  while flips $<$ max_flips **do**
    if t satisfies F **then return** t **else**
      choose a random unsatisfied clause C in F;
      if some variables in C can be flipped without
        breaking any presently satisfied clauses,
        then pick one such variable x at random; else:
      with probability p, pick a variable x in C unif. at random;
      with probability $(1-p)$, do basic GSAT move:
        find a variable x in C whose flipping causes
        largest decrease in the number of unsatisfied clauses ;
      $t \leftarrow (t$ with variable x flipped)
  end while;
  return t.

Novelty+

- WalkSAT can be made greedier using a history-based variable selection mechanism.
- The age of a variable is the number of local search steps since the variable was last flipped.
- Novelty algorithm (McAllester et al., 1997): After choosing an unsatisfiable clause the variable to be flipped is selected as follows:
  - If the variable with the highest score does not have minimal age among the variables within the same clause, it is always selected.
  - Else it is only selected with probability $1-p$, where p is a parameter called noise setting.
  - Otherwise the variable with the next lower score is selected.
  - When sorting variables according to their scores, ties are broken according to decreasing age.
- In Novelty+ (Hoos 1998) a random walk step (with probability wp) is added: with probability $1-wp$ the variable to be flipped is selected according to the Novelty mechanism and in the other cases a random walk step is performed.

Adaptive WalkSat and Adaptive Novelty+

- A suitable value for the noise parameter p is crucial for competitive performance of WalkSAT and its variants.
- Too low noise settings lead to stagnation behaviour and too high settings to long running times.
- Instead of a static setting, a dynamically changing noise setting can be used in the following way:
- Two parameters θ and ϕ are given.
  - At the beginning the search is maximally greedy ($p = 0$).
  - There is a search stagnation if no improvement in the evaluation function value has been observed over the last $m\theta$ search steps where m is the number of clauses in the instance.
  - In this situation the noise value is increased by $p := p + (1-p)\phi$.
  - If there is an improvement in the evaluation function value, then the noise value is decreased by $p := p - p\phi/2$.

Adaptive WalkSat and Adaptive Novelty+

- Notice the asymmetry between increases and decreases in the noise setting.
- Between increases in noise level there is always a phase during which the search progress is monitored without further increasing the noise. No such delay is enforced between successive decreases in noise level.
- When this mechanism of adapting the noise level is applied to WalkSat and Novelty+, we obtain Adaptive WalkSat and Adaptive Novelty+ (Hoos, 2002)
- The performance of the adaptive versions is more robust w.r.t. the settings of θ and ϕ than the performance of the non-adaptive versions w.r.t. to the settings of p.
- For example, for Adaptive Novelty+ setting $\theta = 1/6$ and $\phi = 0.2$ seem to lead to robust overall performance (while there appears to be no such setting for p in the non-adaptive case).

Tools for SAT

- The development of SAT solvers is strongly driven by SAT competitions (`http://www.satcompetition.org/`)
- There is a wide range of efficient solvers also available in public domain.
- See for example `http://www.satcompetition.org/` for solvers that ranked well in previous SAT competitions.
  SAT2005:

  `SatELiteGTI, MiniSAT 1.13, zChaff_rand, HaifaSAT, Vallst, March_dl, kcnf-2004, Dew_Satz1a, Jerusat 1.31 B, Hsat1, ranov, g2wsat, VW`

  SAT-Race 2006:

  `minisat 2.0, Eureka 2006, Rsat, Cadence MiniSat v1.14, ...`

Tools for CSP

- Constraint programming systems offer a rich set of supported constraint types with efficient propagation algorithms and primitives for implementing search.
- Typically the user needs to program, for example, the search algorithm, splitting technique, and heuristic.
- See, for example, `http://4c.ucc.ie/~tw/csplib/links.html` for available constraint solvers:

  `CLAIRE, ECLiPse, GNU Prolog, Oz, Sicstus Prolog, ILOG Solver, ...`

Linear and Integer Programming

- Linear and Integer Programming can be thought to be a subclass of constraint programming where there are
  - two types of variables: real valued and integer valued
  - only one type of constraint: linear (in)equalities.
- Linear Programming (LP): only real valued variables.
- Integer Programming (IP): only integer variables.
- Mixed Integer Programming (MIP): both integer and real valued variables.

Linear and Integer Programming

- Computationally there is a fundamental difference between LP and IP:
  LP problems can be solved efficiently (in polynomial time) but
  IP problems are NP-complete (and all known algorithms have an exponential worst-case running time).
- MIP offers an attractive framework for solving (search and) optimization problems:
  - Continuous variables can be handled efficiently along with discrete variables.
  - Powerful LP solution techniques can be exploited in the IP case through linear relaxation.
  - Bounds on deviation from optimality can be generated even when optimal solutions are not proven.

MIP: Basic Concepts

- In a mixed integer program (MIP) variables are partitioned in two sets such that in the other set (call this I) each variable is required to take an integer value while the remaining variables can take any real value.
- Each variable x_i can have a range $l_i \leq x_i \leq u_i$.
- A linear constraint is an expression of the form

$$a_1 x_1 + \cdots + a_n x_n = b$$

  where the relation symbol '$=$' can also be '$\leq$' or '$\geq$'.
- A linear function is an expression of the form $c_1 x_1 + \cdots + c_n x_n$
- A MIP consists of (i) the objective of minimizing (or maximizing) a linear function, (ii) a set of linear constraints, (iii) ranges for variables and (iv) a set of integer valued variables.

An Example MIP

$\min x_2 - x_1$ s.t.

$$\begin{array}{rcrl} 3x_1 & - & x_2 & \geq 0 \\ x_1 & + & x_2 & \geq 6 \\ -x_1 & + & 2x_2 & \geq 0 \end{array}$$

$2 \leq x_1 \leq 10$

x_2 is integer

MIP: Basic Concepts

- We can write a MIP in the matrix form as follows.
- Let x be a vector of variables $x = (x_1, \ldots, x_n)$.
- Variable ranges can be represented by vectors $l = (l_1, \ldots, l_n)$ and $u = (u_1, \ldots, u_n)$ such that for all i, $l_i \leq x_i \leq u_i$, that is, $l \leq x \leq u$.
- A set of linear constraints $\Sigma_j a_j x_j = b_j$ can be written in matrix form as $Ax = b$ such that $A = (a_{ij})$ is a matrix where a_{ij} is the coefficient for variable j in the ith constraint and $b = (b_1, \ldots, b_n)$.
- A linear objective function $\Sigma_j c_j x_j$ is written as cx where $c = (c_1, \ldots, c_n)$ is a vector of coefficients.
- Then a MIP can be written as:

$$\begin{array}{rl} & \min cx \\ s.t. & Ax = b \\ & l \leq x \leq u \\ & x_j \text{ is integer for all } j \in I \end{array}$$

MIP: Basic Concepts

- A feasible solution to a MIP is an assignment of values to the variables in the problem such that the assignment satisfies all the linear constraints and range constraints and for each variable in I it assigns an integer value.
- A program is feasible if it has a feasible solution otherwise it is said to be infeasible.
- An optimal solution is a feasible solution that gives the minimal (maximal) value of the objective function among all feasible solutions.
- A program is unbounded (from below) if for all $\lambda \in R$ there is a feasible solution for which the value of the objective function is at most λ.

An Example

- Consider the following MIP
  $\min 2x_1 + x_2$ s.t.
  $$\begin{array}{rcrl} 3x_1 & - & x_2 & \geq 0 \\ x_1 & + & x_2 & \geq 6 \\ -x_1 & + & 2x_2 & \geq 0 \\ 2 \leq x_1 & & & \\ x_2 \text{ is integer} & & & \end{array}$$
- $x_1 = 3.1$, $x_2 = 4$ is a feasible solution
- $x_1 = 2$, $x_2 = 4$ is an optimal solution which gives the minimal value (8) for the objective function.
- If the objective is $\min x_1 - x_2$, then the problem is unbounded (from below).
- If we change the range for x_1 to be $x_1 \leq 1$, the problem becomes infeasible.

Modelling: SET COVER

INSTANCE: A family of sets $F = \{S_1, \ldots, S_n\}$ of subsets of a finite set U.
QUESTION: Find an l-cover of U (a set of l sets from F whose union is U) with the smallest number l of sets.

- For each set S_i an integer variable x_i such that $0 \leq x_i \leq 1$
- For each element u of U a constraint

  $$a_1x_1 + \cdots + a_nx_n \geq 1$$

  where the coefficient $a_i = 1$ if $u \in S_i$ and otherwise $a_i = 0$.
- Objective: $\min x_1 + \cdots + x_n$

Modelling: Logical Constraints

- Consider binary integer variables ($0 \leq x_i \leq 1$).
- Disjunction: x_3 has the value of the boolean expression $x_1 \vee x_2$:

  $$\begin{aligned} x_3 &\geq x1 \\ x_3 &\geq x2 \\ x_3 &\leq x_1 + x_2 \end{aligned}$$

- Conjunction: x_3 has the value of the boolean expression $x_1 \wedge x_2$:

  $$\begin{aligned} x_3 &\leq x1 \\ x_3 &\leq x2 \\ x_3 &\geq x_1 + x_2 - 1 \end{aligned}$$

Modelling SAT

Given a SAT instance F in CNF, introduce

- for each Boolean variable x in F, a binary integer variable x $(0 \leq x \leq 1)$.
- for each clause $l_i \vee \cdots \vee l_n$ in F, a constraint

$$a_1x_1 + \cdots + a_nx_n \geq 1 - m$$

  where the coefficient $a_i = 1$ if the literal l_i is positive and otherwise $a_i = -1$ and m is the number of negative literals in the clause.
- Then F is satisfiable iff the corresponding set of constraints has a feasible solution.