



Changing the rules of business™



**Using Genetic
Algorithms
in ILOG Solver**

CPAIOR '05

Order of business

- **EAs in ILOG Solver**
- **Example problem: bin packing**
- **Direct and indirect representations**
- **Creating initial populations**
- **Selection and evolution**
- **CP-based intensification**
- **Some results**

What is Solver?

- **A C++ Library for constraint programming**
 - **Many constraint types with powerful propagation**
 - **Extensible**
 - New constraints
 - New search strategies
- **Solver IIM (Iterative Improvement Methods)**
 - **Local search & evolutionary algorithms**
 - **Extensible**
 - New local search neighborhoods
 - New evolutionary operators

EAs in ILOG Solver IIM 6.1



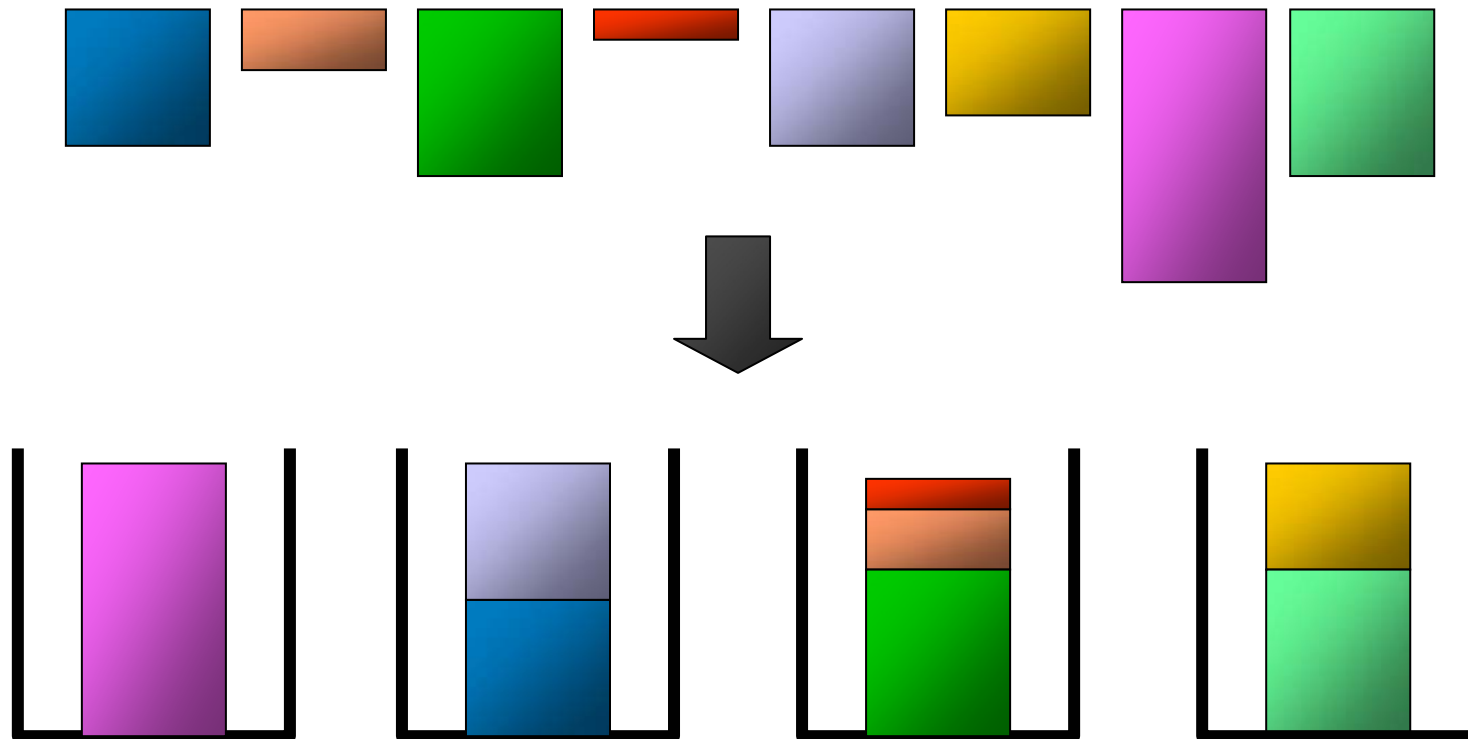
Basics

- **For constrained optimization problems**
- **Solution and solution pool objects**
 - **One solving engine, many solution objects**
- **Solution pool operator**
 - **Takes a set of solutions and instantiates constrained variables according to operator**
- **Solution pool processor**
 - **As operator, but generates solution objects**
- **Solution selectors, comparators, evaluators**

Example: Bin Packing

Problem

- Pack a set of n items of weight $w(i)$ into a minimum number of bins, each of capacity C



Example: Bin Packing



Model

IloEnv env Environment: serves as a global object manager
IloIntArray weight Array of object weights (sorted non-increasing)
IloInt cap Capacity of the bins

```
(1) IloInt numItems = weight.getSize();  
(2) IloInt numBins = numItems;  
(3) IloIntVarArray where(env, numItems, 0, numBins - 1);  
(4) IloIntVarArray load(env, numBins, 0, cap);  
(5) IloInt lb = (IloSum(weight) + cap - 1) / cap;  
(6) IloIntVar used(env, lb, numBins);  
(7) IloModel model(env);  
(8) model.add(IloPack(env, load, where, weight, used));
```

Example: Bin Packing



Constructive method

- **Decreasing first fit**
 - **Consider items according to decreasing weight**
 - **Place each item in the first bin with enough space**
 - **On failure, disallow item from this first bin**
- **Implementation**
 - **Sort “where” vars. by decreasing object weight**
 - **Instantiate these variables in the given order**
 - Choose minimum value for variable (first available bin)
 - **Implemented using `IloGenerate` of Solver**

Representations

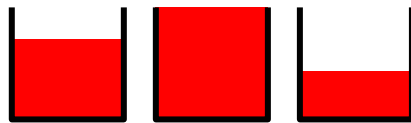


- **Direct: work directly on decision variables**
 - chromosome = decision variable (“where” var.)
 - Normally use *custom* genetic operators
 - For bin packing, use a “grouping operator”
- **Indirect: work on new additional variables p**
 - Here, these vars. assign a priority to each item
 - Run EA on priorities using classic operators
 - *Decode* priorities to “where” variables
 - Decode = DFF except priorities replace weights

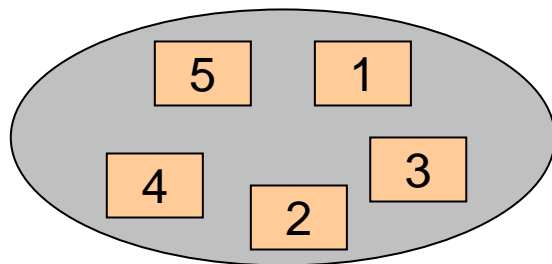
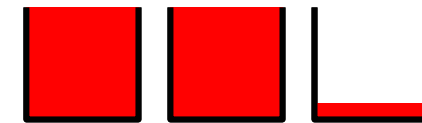
Representations



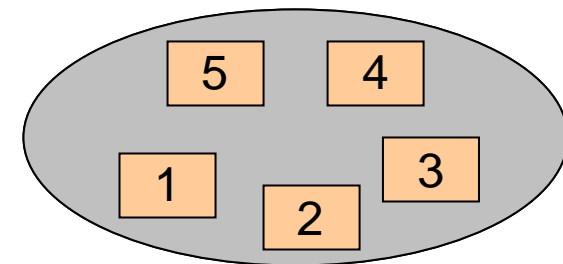
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Genetic Operator



Genetic Operator



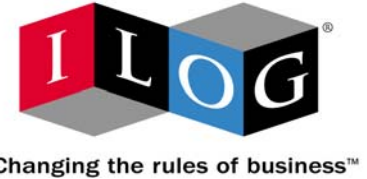
decodes to



decode



Initial Population



Direct representation

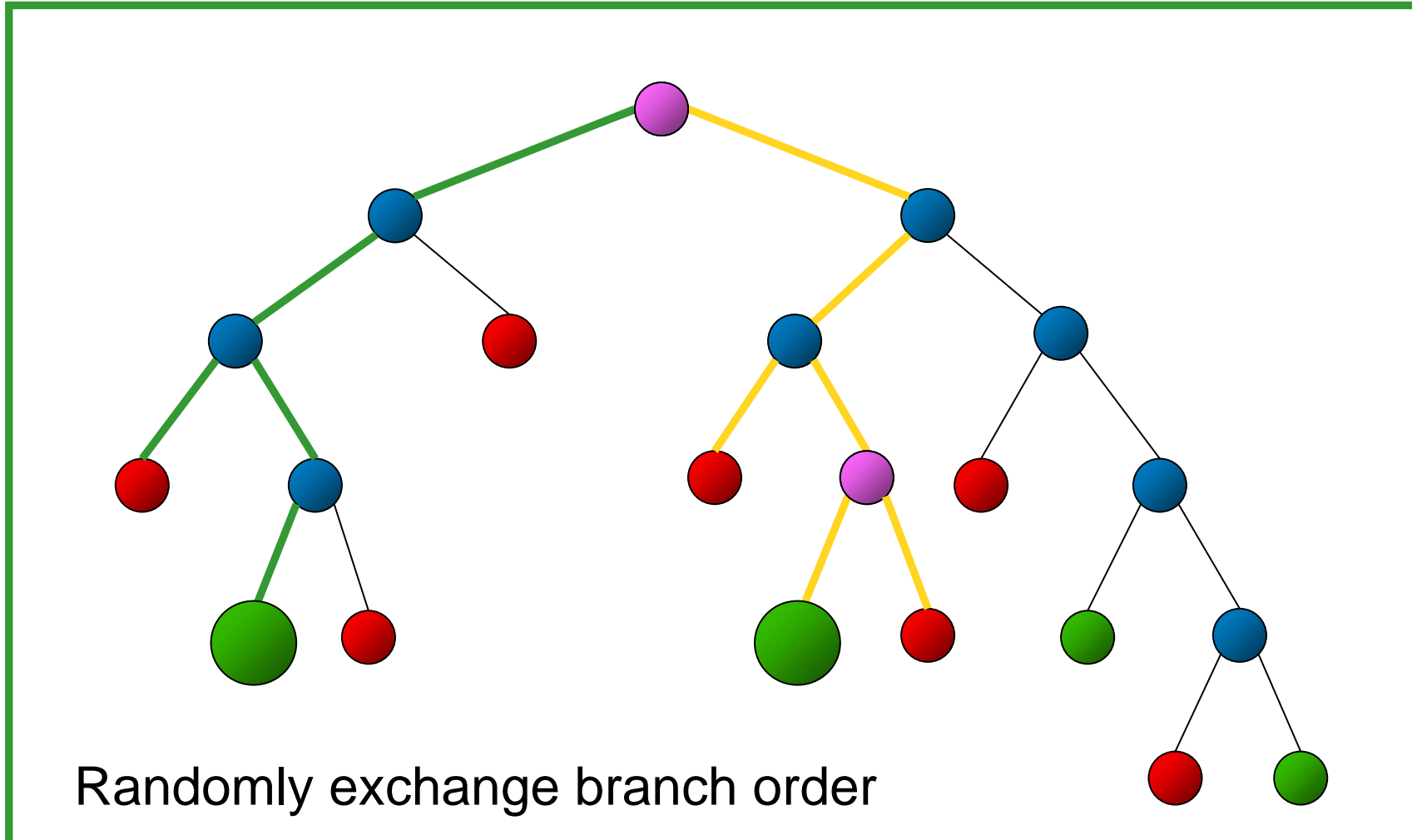
- **Constraints discount random solutions**
- **Use a constructive search for first solution**
 - **Diversity: use a *random* variable / value choice**
 - **Restart search after limit is node reached**
 - **Downside: random solutions often poor**
- **Can we trade quality vs. diversity?**
 - **Yes. If we have a “good” search strategy**
 - **Mix a “good” CP search with a random one**

Initial Population



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Tree search perturbation



Initial Population



Direct Representation

```
(1) IloSolution prototype(env);
(2) prototype.add(where);
(3) prototype.add(load);
(4) prototype.add(used);
(5) prototype.add(IloMinimize(env, used));

(6) IloSolutionPool popn(env);

(7) IloGoal dff = IloGenerate(env, where);
(8) IloGoal packGoal = IloRandomPerturbation(env, dff, 0.3);

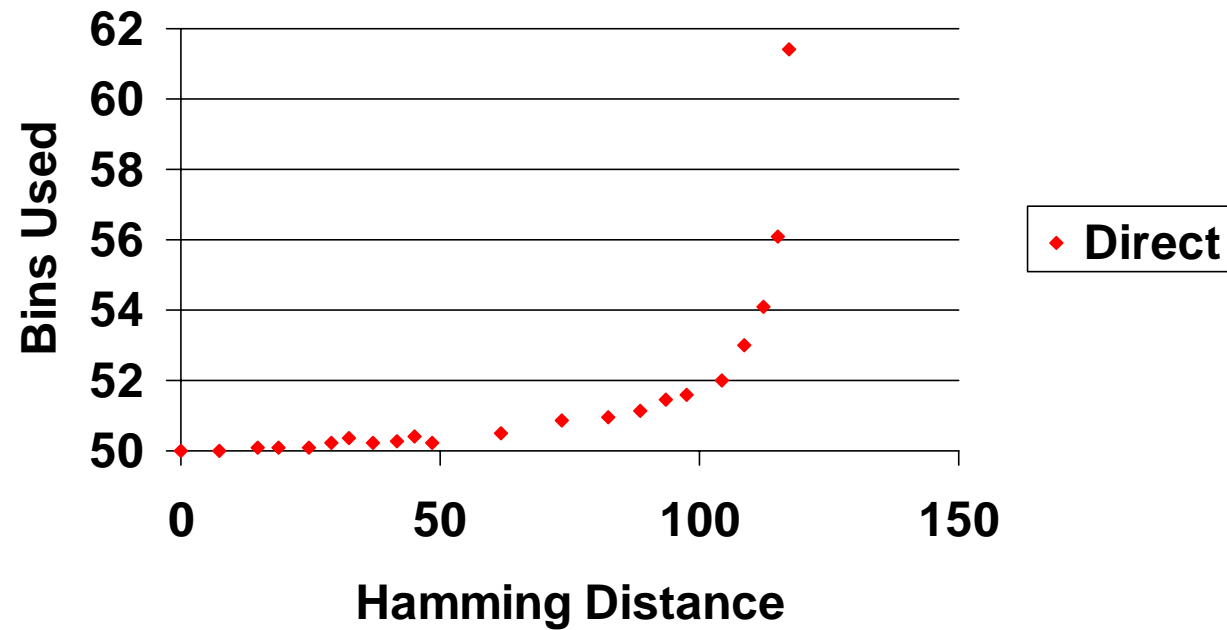
(9) IloPoolProc source = IloSource(env, packGoal, prototype);
(10) IloPoolProc initPop = source(popSize) >> popn;
(11) IloSolver solver(model);
(12) solver.solve(IloExecuteProcessor(env, initPop));
```

Initial Population Diversity



Controlling diversity

Diversity / Cost Correlation



Evolve the population



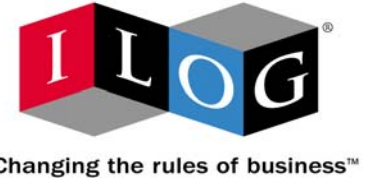
Direct representation

```
(1) IloPoolOperator xo = XOperator(env, load, where, weight, used);
(2) xo = IloLimitOperator(env, xo && packGoal, IloFailLimit(env, 100));

(3) IloRandomSelector<IloSolution, IloSolutionPool> rndSelector(env);
(4) IloPoolProc evolve = popn
(5)     >> IloSelectSolutions(env, rndSelector)
(6)     >> xo(popSize / 3)
(7)     >> IloReplaceSolutions(env, popn)
(8)     >> IloDestroyAll(env);

(9) IloInt best = popn.getBestSolution().getObjectiveValue();
(10) for (IloInt i = 0; i <= maxGen && best > lb; i++) {
(11)     env.out() << "Generation " << i << ": " << best << endl;
(12)     solver.solve(IloExecuteProcessor(env, evolve));
(13)     best = popn.getBestSolution().getObjectiveValue();
}
```

Crossover operator



Direct representation

- **Idea: child inherits well packed bins from a parent**
 - All items not in well-packed bins are repacked
 - Suppose we have a solution using m bins
 - For *better* solutions, bins need a mean load of $W / (m - 1)$
- **Algorithm**
 - Consider bins in a random order
 - Inherit *all* items from the bin of one (random) parent if none of these items has been added to the child
 - Stop when “enough” bins have been inherited
 - (Complete the packing using Decreasing First Fit)

Crossover operator: code



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Direct representation

```
ILOIIMOP4(XOOperator, 2, IloIntVarArray, load, IloIntVarArray, where,
          IloIntArray, weight, IloIntVar, used) {
    IloSolver solver = getSolver();
    IloInt numBins = load.getSize();
    IloSolutionPool parents = getInputPool();
    IloInt numBinsUsed = IlcMax(parents[0].getValue(used), parents[1].getValue(used)) - 1;
    IloInt reqdMeanLoad = (IloSum(weight) + numBinsUsed - 1) / numBinsUsed;
    IlcRandom rnd = solver.getRandom();
    IlcIntArray order(solver, numBins);
    MakeRandomOrder(order, rnd);
    IloInt toDo = rnd.getInt(numBinsUsed);

    for (IlcInt i = 0; i < numBins && toDo > 0; i++) {
        IlcInt bin = order[i];
        IlcBool good0 = parents[0].getValue(load[bin]) >= reqdMeanLoad &&
            AllItemsUnpacked(solver, parents[0], bin, where);
        IlcBool good1 = parents[1].getValue(load[bin]) >= reqdMeanLoad &&
            AllItemsUnpacked(solver, parents[1], bin, where);
        if (good0 || good1) {
            IloSolution soln = parents[!good0 || (good1 && rnd.getInt(2))];
            PackAllItems(solver, soln, bin, where);
            toDo--;
        }
    }
    return 0;
}
```


Initial Population



Indirect representation

- **Priorities are unconstrained**
 - **Random solutions will do just fine!**
 - **Decode each set of priorities into a packing**
 - Backtracking decoder respects constraints
- **Again, can we trade off quality vs. diversity?**
 - **Yes. If we know a good set priorities**
 - **Can prioritize items according to weight**
 - **Mix “good priorities” with random ones**

Indirect representation

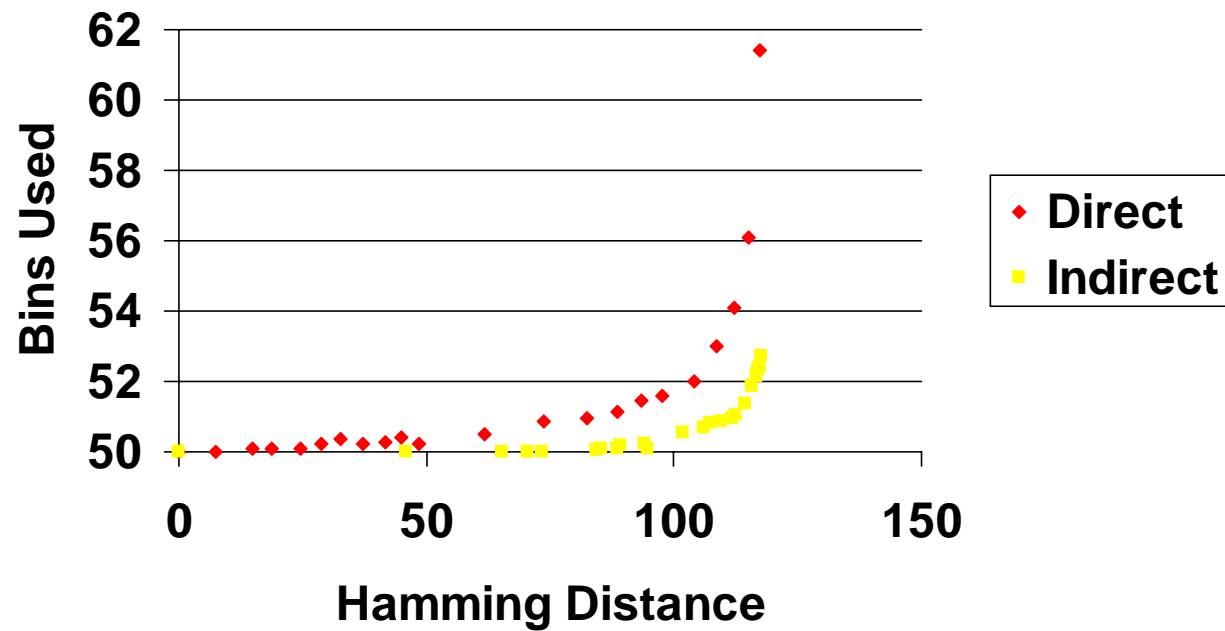
- **Decoder: pack items in priority order**

```
(1) ILCGOAL2(Decode, IlcIntArray, prio, IlcIntArray, where) {  
(2)   IlcInt best = -1;  
(3)   for (IlcInt i = 0; i < where.getSize(); i++) {  
(4)     if (!where[i].isBound() &&  
(5)       (best < 0 || prio[i].getValue() > prio[best].getValue()))  
(6)       best = i;  
(7)   }  
(8)   if (best >= 0)  
(9)     return IlcAnd(IlcInstantiate(where[best]), this);  
(10)  return 0;  
(11) }
```

Initial Population Diversity

Controlling diversity

Diversity / Cost Correlation



Evolve the population



Indirect representation

```
... IloIntArray priority(env, 0, maxPriority);
    IloGoal decode = Decode(env, priority, where); ...

(1) IloEAOperatorFactory f(env, priority);
(2) f.setSearchLimit(IloFailLimit(env, 100));
(3) f.setAfterOperate(decode);

(4) IloPoolProcArray ops(env);
(5) ops.add(f.uniformXover());
(6) ops.add(f.mutate(4.0 / numItems);
(7) IloRandomSelector<IloPoolProc, IloPoolProcArray> rndSelector(env);
(8) IloPoolProc breed = IloSelectProcessor(env, ops, rndSelector);
(9) IloPoolProc gen = popn
(10)         >> IloSelectSolutions(env, rndSelector)
(11)         >> breed(popSize / 3)
(12)         >> IloReplaceSolutions(env, popn)
(13)         >> IloDestroyAll(env);
```

Packing quality measure



Indirect representation

- For equal numbers of bins, better quality packings have bigger chunks of free space

```
(1) ILOEVALUATOR2(PackQuality, IloSolution, s,  
(2)             IloIntArray, load, IloInt, cap) {  
(3)   IloNum q = 0;  
(4)   for (IloInt i = 0; i < load.getSize(); i++) {  
(5)     IloInt ld = s.getValue(load[i]);  
(6)     if (ld != 0)  
(7)       q += (cap - ld) * (cap - ld);  
(8)   }  
(9)   return q;  
(10) }
```

Finer replacement method

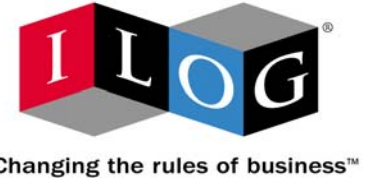


Indirect representation

```
(1) IloEvaluator<IloSolution> quality = PackQuality(env, load, cap);
(2) IloEvaluator<IloSolution> cost = IloSolutionEvaluator(env, used);
(3) IloComparator<IloSolution> compareWorst = IloComposeLexical(
(4)     cost.getGreaterThanComparator(),
(5)     quality.getLessThanComparator()
(6) );
(7) IloSolutionPoolSelector selectDead =
(8)     IloBestSelector<IloSolution, IloSolutionPool>(compareWorst);

(9) IloPoolProc gen = popn
(10)     >> IloSelectSolutions(env, rndSelector)
(11)     >> breed(popSize / 3)
(12)     >> IloReplaceSolutions(env, popn, selectDead)
(13)     >> IloDestroyAll(env);
```

CP-based intensification



Using quality constraints

- **Cost UBs can help tree search find better solutions**
 - **When completing the child in a direct representation**
 - **When decoding an indirect representation**
 - **Child is forced to be at least as good as worst parent**

```
xo = IloImproveOn(env, used, 0.5) && xo;
```

```
ILOIIMOP2(ImproveOn, 1, IloIntVar, used, IloNum, p) {  
    IloInt lim = getInputPool().getWorstSolution().getObjectiveValue();  
    IloSolver solver(getSolver());  
    solver.add(used <= limit - (solver.getRandom().getFloat() < p));  
    return 0;  
}
```

Some results



- Population size = 30, 1 minute time limit
- Falkenauer's 120 item problems (20 instances)

Representation	+cp intens	+ quality	# optima
Direct	N	N	15
Direct	N	Y	19
Direct	Y	N	20
Direct	Y	Y	20
Indirect	N	N	9
Indirect	N	Y	15
Indirect	Y	N	17
Indirect	Y	Y	19

Summary



- **ILOG Solver IIM has EA for constraint optimization**
 - Use standard CP search as a base
- **Support for direct and indirect representations**
- **Selectors/evaluators/comparators**
- **You can define your own operators**
 - Operators can perform a local search, or LNS
- **CP brings fundamental advantages**
 - Can *directly* tackle constrained problems
 - Decoding simplicity in the presence of side constraints
 - Constraint-based acceptance criteria

Create an initial population



Indirect representation: code

```
(1) const IloInt maxPriority = IloMax(weight);
(2) IloGoal decode = Decode(env, priority, where);
(3) for (IloInt i = 0; i < popSize; i++) {
(4)     IloSolution soln = prototype.makeClone(env);
(5)     for (IloInt j = 0; j < numItems; j++) {
(6)         IloInt prio = weight[j];
(7)         if (env.getRandom().getFloat() < 0.1)
(8)             prio = 1 + env.getRandom().getInt(maxPriority);
(9)         soln.setValue(priority[j], prio);
(10)    }
(11)    IloGoal evaluate = IloRestoreSolution(env, soln)
(12)                        && decode
(13)                        && IloStoreSolution(env, soln);
(14)    solver.solve(evaluate);
(15)    popn.add(soln);
(16) }
```