

Routing Optimisation with OscaR.cbls and some context

OscaR v4.0 - Spring 2017

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TSP is often polynomial (joke?)

Academia:

- Given
 - the distance matrix
- Find
 - The cheapest permutation

- In the real world:
 - You have to compute the distance matrix
 - 100 points leads to ~10k distance
 - 0.1 sec per distance leads to 16 minutes



CETIC Research and Tech transfer

- Staff: 42
- Budget 2015: 4.8 M€
- Three research department:
 - Software & System Engineering
 - Software engineering, formal methods, code analysis, algorithmic, optimization, requirements engineering
 - Software and service technologies
 - Cloud computing, distributes architectures, data management
 - Embedded and Communication Systems
 - IoT, heterogeneous hardware architectures
- Two economical activities:
 - Research projects:
 - H2020, Cornet, Regional, etc
 - Service to industry.
 - custom, short term, paid by company, IP transferred



History of OscaR.cbls

- PIPAs project: Job-shop scheduling
 - Lot of budget; develop a CBLS engine with iFlatRelax: Asteroïd
- Merging code base with Scampi (Pierre Schaus): OscaR
- Service on routing optimization, delivered wit GoogleCP
- SimQRi research project: Cornet
 - Research on how to represent search strategies, notion of combinators
- Service on Routing optimization round2:
 - Generating the distance matrix (a lot of work)
 - with traffic jam
 - Lots of algorithmic there (closed source, NDA)
 - Switching to OscaR.cbls (not so much work)
 - Because GoogleCP could not handle traffic jams
 - Speed improvement,
 - routing neighbourhoods into combinator framework



- Internships: symmetry elimination, parallel propagation, routing, bin packing, PDP, etc.
- Ongoing projects with OscaR.cbls:
 - SAMOBI research project
 - Sequence variable, refreshing the routing engine, PDP
 - H2020 TANGO
 - Flexible job-shop
 - 2 Regional
 - Large capacitated warehouse with additional constraints
 - Routing /scheduling stuff (not clear yet)
 - Cornet
 - Stochastic scheduling
 - (?factory scheduling?, eval ongoing)
- Tutorial ongoing



Oscar

- Open source framework for combinatorial optimization
- CP CBLS, MIP, DFO engines
- Open source LGPL license
 - https://bitbucket.org/oscarlib/oscar
 - Implemented in Scala
- Consortium
 - CETIC, UCL, N-Side Belgium
 - Contributions from UPPSALA Sweden



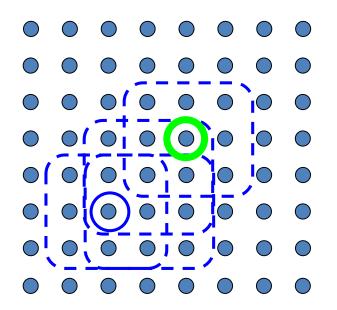


- Introduction
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 - OscaR.Cbls
- Using OscaR.cbls
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 - Modelling
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 - A simple example
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- Some fun, in case you have questions



Local search in one slide

TSP : all the possible tours n cities; (n-1)! tours



Point in the search space

Some black magic required to escape from local minima

TSP: random tour?

Pick an initial solution

Repeat

Explore neighborhood

Move to best neighbor

Until no better neighbor

TSP: moving a city to another position in the tour Current state: $a \rightarrow b \rightarrow c \rightarrow d \rightarrow e \rightarrow a$ Moving city c yields three neighbors: $a \rightarrow c \rightarrow b \rightarrow d \rightarrow e \rightarrow a$ $a \rightarrow b \rightarrow d \rightarrow c \rightarrow e \rightarrow a$ $a \rightarrow b \rightarrow d \rightarrow e \rightarrow c \rightarrow a$

 $O(n^2)$ neighbors when considering all cities



The basic equation of local search

Local search—based solver = model + search procedure

Defines variables constraints Objectives

Neighborhoods That modify some variables of the problem

...



The uncapacitated warehouse location problem

Given

- S: set of stores that must be stocked by the warehouses
- W: set of potential warehouses
 - Each warehouse has a fixed cost f_w
 - transportation cost from warehouse w to store s is c_{ws}

Find

- O: subset of warehouses to open
- Minimizing the sum of the fixed and the transportation cost.

$$\sum_{w \in O} f_w + \sum_{s \in S} \min_{w \in O} (c_{ws})$$



Notice

A store is assigned to its nearest open warehouse



val it = *neighborhood*.doAllMoves(*obj*)

A WLP solver written with neighbourhood combinators

```
val m = new Store()
val warehouseOpenArray = warehouses.map(
                           CBLSIntVar(m, 0 \text{ to } 1, 0, "warehouse" + _ + "")).toArray
val openWarehouses = Filter(warehouseOpenArray)
val distanceToNearestOpenWarehouse = stores.map(
         min(distanceCost(), openWarehouses,
                           defaultCostForNoOpenWarehouse)).toArray
val obj = Objective(Sum(distanceToNearestOpenWarehouse)
                  + Sum(costForOpeningWarehouse, openWarehouses))
m.close()
val neighborhood = (BestSlopeFirst(List(
                       AssignNeighborhood(warehouseOpenArray, "SwitchWarehouse"),
                       SwapsNeighborhood(warehouseOpenArray, "SwapWarehouses")),
                   onExhaustRestartAfter(
                       RandomizeNeighborhood(warehouseOpenArray, W/10), 2, obj))
```



Local search is (most of the time) black magic!

- Non exhaustive
 - Seldom proof of optimality, only benchmarking
- Needs tuning:
 - Neighborhood rule
 - What neighborhood? What parameters?
 - Modeling
 - · Soft, hard, implicit, automatic constraint?
 - Meta-heuristics
 - When to call neighborhoods? tabu? Restart? Simulated annealing?
- ... But it (can) work
 - 3-opt for TSP <3% to optimum in practice!!</p>
 - iFlatiRelax <1% to optimality for cumulative jobShop
- → Need for benchmarking, tuning, etc

OscaR.cbls is about making this quick, so you can get the most of your algorithm



Local search is (most of the time) black magic!

Local search is black magic or spell inventors · you are wizards...

Jam a wand maker with my team.., so you \rightarrow 1



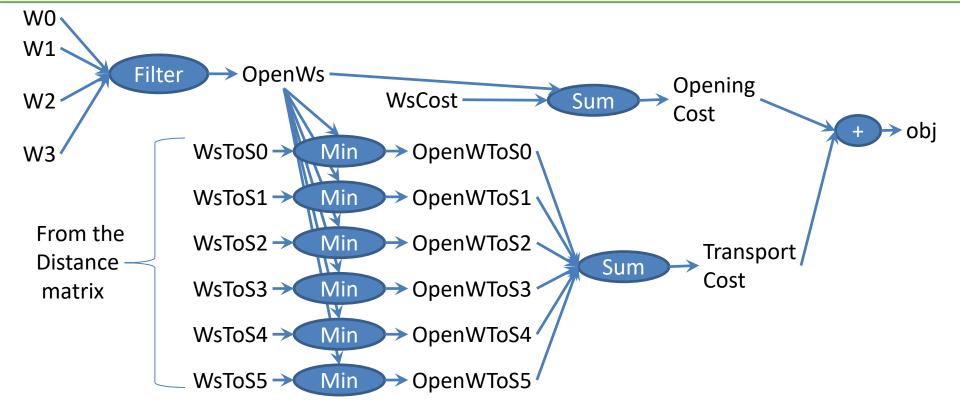
Modeling Support with OscaR

- Three types of variables
 - IntVar, SetVar, and SeqVar
- Invariant library
 - -Logic:
 - Access on array of Int/SetVar, Filter, Cluster, etc.
 - -MinMax:
 - Min, Max, ArgMin, ArgMax
 - -Numeric:
 - Sum, Prod, Minus, Div, Abs, etc.
 - -Set:
 - Inter, Union, Diff, Cardinality, etc.
 - -Seq:
 - Concatenate, Size, Content, etc.
 - –Routig on Seq:
 - Constant Distance, Node-Vehicle restrictions, etc.

Summing up to roughly 100 invariants in the library



A quick look under the hood: Propagation graph for the WLP(4,6)



Propagation: update the output(s) to reflect a change on the inputs

- Single wave: elements are touched at most once
- Incremental: all invariants update their outputs incrementally
- Selective: only things that need to be updated wrt. changes are updated
- Partial: only things contributing to the needed output are updated
 Automatic when using objectives, so mostly you do not have to worry about that



Search support with OscaR

- Three sets of neighbourhoods
 - Domain-independent: assign, swap, flip, roll, shift, etc.
 - Routing: one point move, 2-opt, 3-opt, insert point, etc.
 - Scheduling: flatten, relax

lots of tuning: symmetry elimination, hot restart, best/first, search zone, etc.

- Neighbourhood combinators
 - Selecting neighbourhood
 - Stop criteria
 - Solution management
 - Meta-heuristics: restart, simulated annealing
 - Combined neighbourhood: cross-product "AndThen", linear aggregation
 - Graphical display of objective function vs. run time
- Can also use customized search procedure based on linear selectors



etic Three shades of Warehouse Location

All Assigns, all swaps, all assigns, etc

... with best move for switch

Tabu search (requires model extension)



Modelling

- The sequence variable
- Library of invariants
- Searching
 - Library of neighbourhoods
 - Compatible with our combinators
- Example
 - Simple benchmark VRP
 - A complex search strategy for deliveries

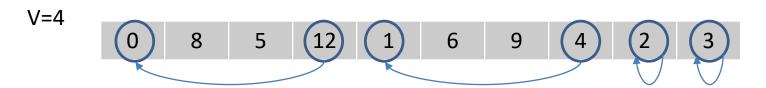


New sequence variable, for routing

- Why? SPEED & GENERICITY!!
 - Efficient representation of moves in the sequence
 - Symbolic information on moves & check pointing
 - Makes it possible to develop efficient constraints and invariants
 - Library of efficient constraint and invariants,
 - Routing: distance matrix, node-vehicle restriction, etc.
 - Standard: size, content, flip, append, etc.

• Dedicated, efficient data-structures





- All vehicle in the same sequence variable
- Vehicle [0..v-1] start from nodes [0..v-1]
- Vehicle starts are always in the sequence in that order
- Vehicle implicitly come back to their start point
 - All invariants use this assumption
 - You can "tune" distance matrices if it is not the case
- Vehicle starts cannot be moved
 - But you can of course move all other nodes
- At most one occurrence of every value in the sequence



Routing: an (optional) VRP class

```
class MySimpleRoutingWithUnroutedPoints(n:Int, v:Int,
       symmetricDistance:Array[Array[Int]], m:Store, maxPivot:Int)
  extends VRP(n, v, m, maxPivot)
                                    traits that add standard features.
  with ClosestNeighbors{
                                     You can also add features in the class below
  override def getDistance(from:Int,to:Int):Int=
     symmetricDistance(from) (to)
  val penaltyForUnrouted = 10000
  val routed = Content(routes.createClone(50))
  val unrouted = Diff(CBLSSetConst(SortedSet(nodes: *)),
                     routed)
  val totalDistance = ConstantRoutingDistance(routes, v ,false,
                            symmetricDistance, true) (0)
  val obj = Objective(totalDistance +
                     (penaltyForUnrouted*(n - Size(routes))))
  val closestNeighboursForward = computeClosestNeighborsForward()
  def size = routes.value.size
```



Main routing invariants (1/2)

- ConstantRoutingDistance
 - given a distance matrix,
 - maintains the driven distance
 - options: isSymmetric? perVehicle? preCompute?
 - O(1) update on classical neighbourhoods (with proper options)
- ForwardCumulativeIntegerDimensionOnVehicle
 - given a function (node × content × node') =>content'
 - maintains an array node=>content
- ForwardCumulativeConstraintOnVehicle
 - given
 - a function (node × content × node') =>content'
 - a max capacity
 - maintains a violation per vehicle (sum of overshoot per node)
- NodesOfVehicle
 - given route
 - maintains vehicle => set of nodes reached by vehicle



Main routing invariants (2/2)

- NodeVehicleRestrictions
 - given set of couples (node, vehicle)
 - maintains number of such couples (n,v) such that vehicle v reaches node n
 - O(1) update on classical neighbourhoods!
- RouteSuccessorAndPredecessors
 - given route
 - maintains two IntVar arrays: node => predecessor, node => successor
 - you can declare virtually anything from these arrays, using element invariant
- VehicleOfNodes
 - given route
 - maintains a SetVar array: vehicle => nodes reached by vehicle



Routing neighbourhoods

- InsertPoint
 - InsertPointRoutedFirst:

```
for(r <- routed)
  for(u <- unrouted relevant wrt r)</pre>
```

InsertPointUnroutedFirst

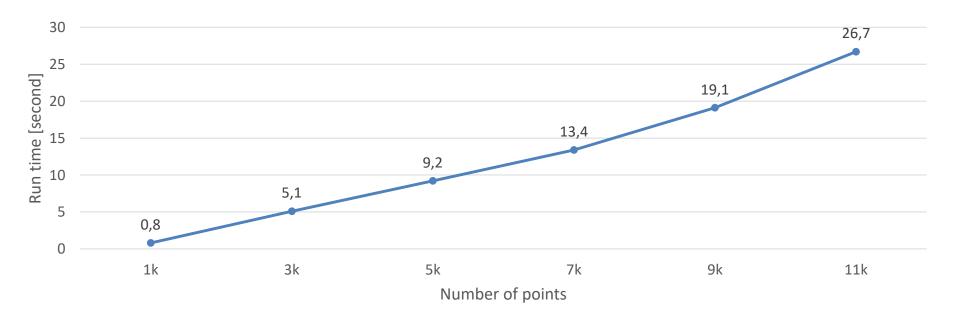
```
for(u <- unrouted)
  for(r <- routed relevant wrt u)</pre>
```

...

- OnePointMove
- RemovePoint
- SegmentExchange
- ThreeOpt
- TwoOpt
 - TwoOpt1
 - TwoOpt2

Symetric VRP (v = 100) N vs. run time

Median over 10 runs with symmetric distance: square map with randomly placed points and straight line distance





Another example of search strategy

- Basic Problem: routing a tanker truck
 - Serve as many customers as possible
 - Need to refill at depot to serve more customer
- Problem: inserting depot pass is not desirable
- Solution: insert depot and additional customer at the same time to make it desirable
 - Dedicated two-point-insert, built through cartesian product of neighbourhoods





Comet

- First CBLS implem by pascal van Hentenryck
- Not maintained since 2008?
- Kangaroo
 - One paper @CP2011, status unknown, not available
- LocalSolver
 - Commercial tool, with acad licence
 - Only Booleans and floats, very few invariants
 - Closed search procedure, closed source
- EasyLocal++
 - No support for modelling
- GoogleCP
 - Not a CBLS tool; a CP engine mimicking CBLS, less scalability
- InCell
- Lion



Conclusion: Features of Oscar.cbls

- Modelling part: Rich modelling language
 - IntVar, SetVar, SeqVar
 - ~100 invariants: Logic, numeric, set, min-max, etc.
 - 17 constraints: LE, GE, AllDiff, Sequence, etc.
 - Constraints can attribute a violation degree to any variable
 - Model can include cycles
 - Fast model evaluation mechanism
 - Efficient single wave model update mechanism
 - · Partial and lazy model updating, to quickly explore neighbourhoods
- Search part
 - Library of standard neighbourhoods
 - Combinators to define your global strategy in a concise way
 - Handy verbose and statistics feature, to help you tuning your search
- Business packages: Routing, scheduling
 - Model and neighbourhoods
- FlatZinc Front End [Bjö15]
- 49kLOC



Who is behind OscaR.cbls?

- CETIC team
 - Renaud De Landtsheer
 - Yoann Guyot
 - Fabian Germeau
 - Gustavo Ospina
 - Christophe Ponsard
- Contributions from Uppsala
 - Jean-Noël Monette
 - Gustav Björdal
- Internships & MS Theses
 - UMONS: Gaël Thouvenin, Sébastien Drobisz, Florent Ghilain, Jannou Bohée
 - IPL: Fabian Germeau
 - HENALUX: Quentin Wautelet













- Repository / source code
 - https://bitbucket.org/oscarlib/oscar/wiki/Home
- Released code and documentation
 - https://oscarlib.bitbucket.org/
- Discussion group / mailing list
 - https://groups.google.com/forum/?fromgroups#!foru m/oscar-user

Two typical remarks on OscaR.cbls

 Why don't you use C/C++ with templates, and compile with gcc -o3? You would be 2 times faster!

 I can develop a dedicated solver that will run 2 times faster because it will not need the overhead data structures of OscaR.cbls

... these remarks are correct, but ...



Brain cycle is more valuable than CPU cycle

- Algorithmic tunings deliver more than 2 to 4!
 - Ex: symmetry elimination on neighbourhoods
 - Ex: Restricting your neighbourhood to relevant search zones
 - Ex: Tuning when your neighbourhoods are actually used
 - We lately had a speedup 10 by tuning a search procedure
- Our framework cuts down dev cost,
 so you have time to focus on these high-level tunings!
- TODO: parallel propagation
 - Goal: same "basic speed" as dedicated implem
 - A core is cheaper than a single day of work for an engineer

In the real world, solving optimization problems using exact methods is a waste of resources