

# A good recipe for solving MINLPs

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# Summary of Talk

## 1 The Problem

## 2 The Ingredients

VNS

Local Branching

Branch-and-Bound for cMINLPs

Sequential Quadratic Programming

## 3 The RECIPE

## 4 MINLPLib

## 5 Computational Experiments

## 6 Conclusions

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# Problem Classes

- We distinguish four classes of mathematical programs:
  - ① Linear Programs (LPs)
  - ② Mixed-Integer Linear Programs (MILPs)
  - ③ Nonlinear Programs (NLPs)
  - ④ Mixed-Integer Nonlinear Programs (MINLPs)
- For nonlinear programs, convexity of objective function and constraints is also important to determine the problem's difficulty

# A Difficult Task

- We address the most difficult problem class: nonconvex MINLPs
- Obviously, this class is also the most expressive
- Difficulties arise from both nonconvexity and integrality
- We cannot aim for optimality, hence we would easily settle for a *fast* and *reliable* heuristic (who would not?)
- Especially true for industrial applications: we need something that is easy to use and does not need hundreds of parameters

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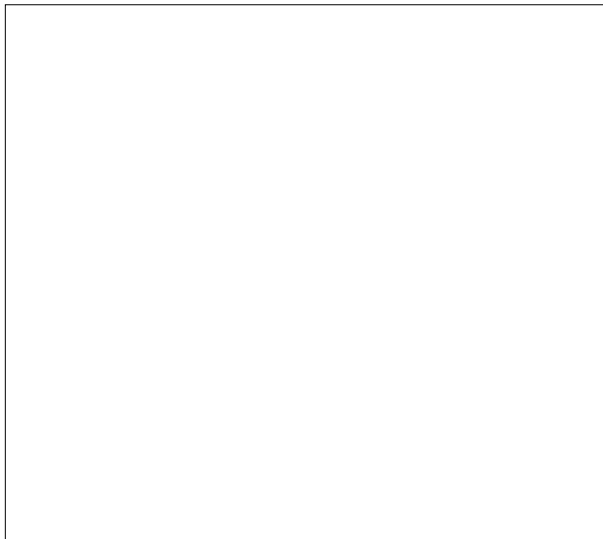
## 5 Computational Experiments

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# VNS: Introduction

- Applicable to discrete and continuous problems
- Uses any local search as a black-box
- In its basic form, easy to implement
- Few configurable parameters
- Used for a variety of problem, large amount of references [Hansen and Mladenović, 2001]

# VNS: Algorithm (sketch)



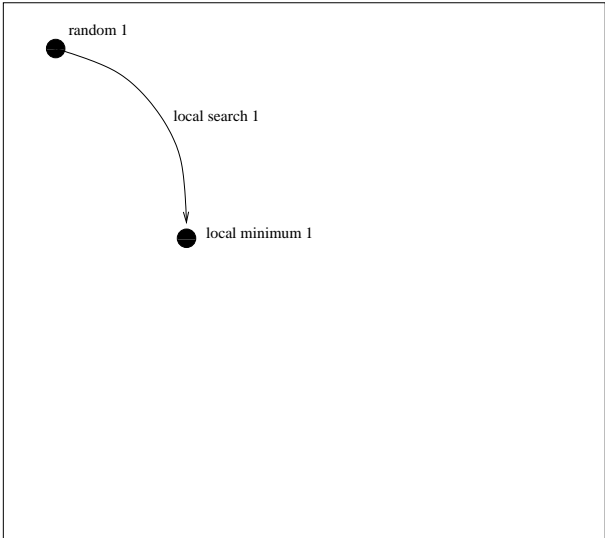


# VNS: Algorithm (sketch)

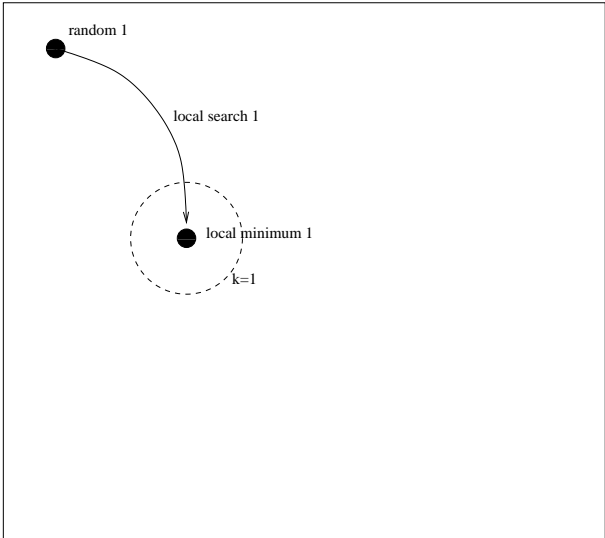


random 1

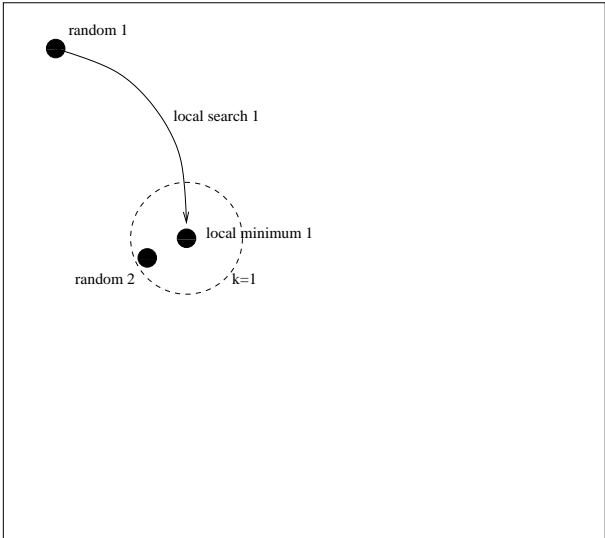
# VNS: Algorithm (sketch)



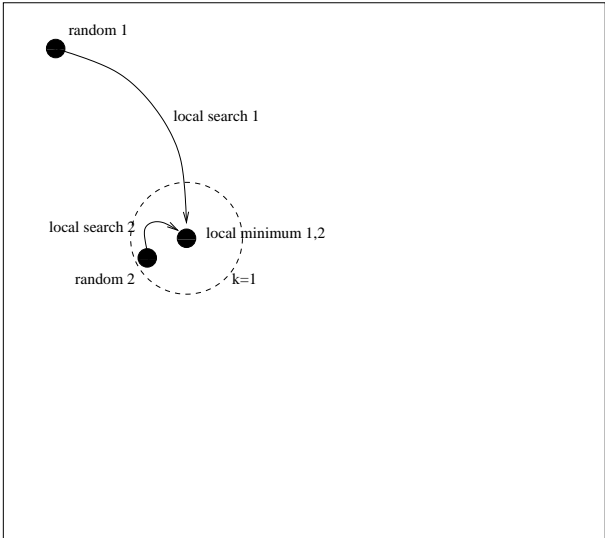
# VNS: Algorithm (sketch)



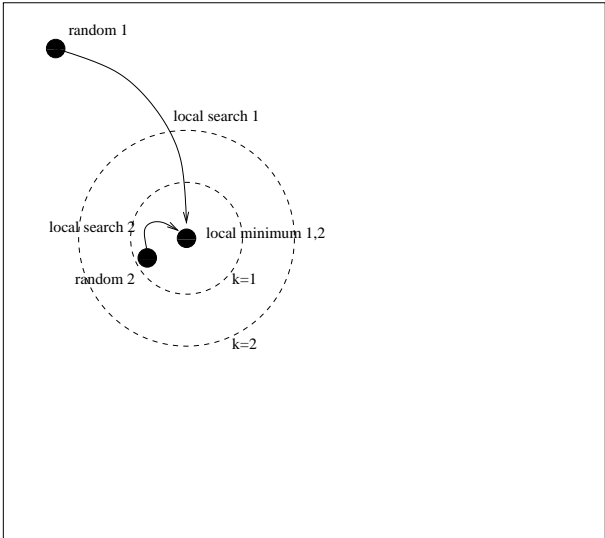
# VNS: Algorithm (sketch)



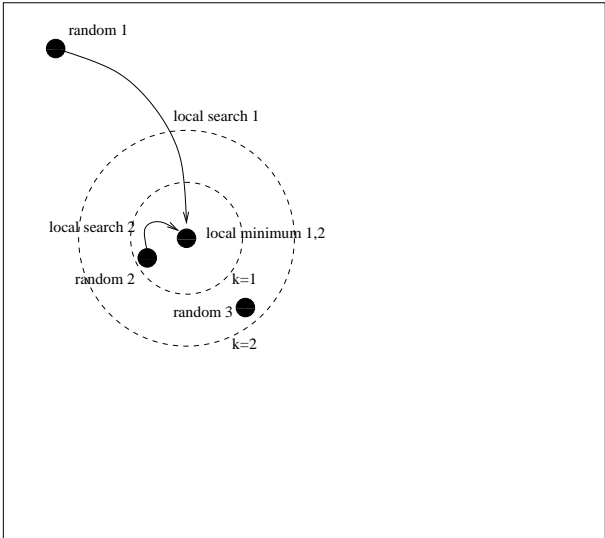
# VNS: Algorithm (sketch)



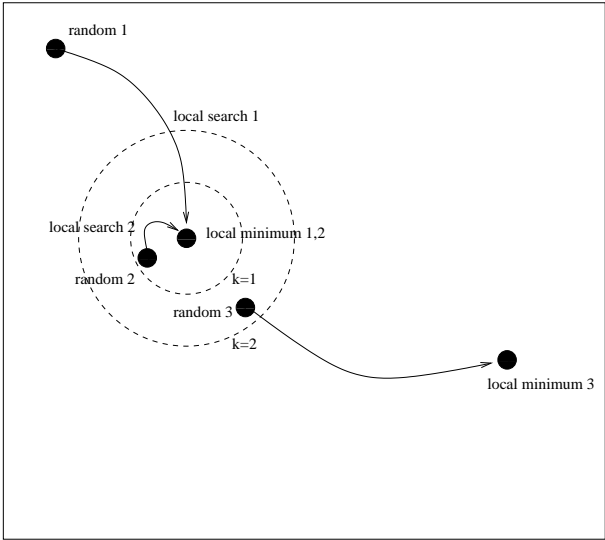
# VNS: Algorithm (sketch)



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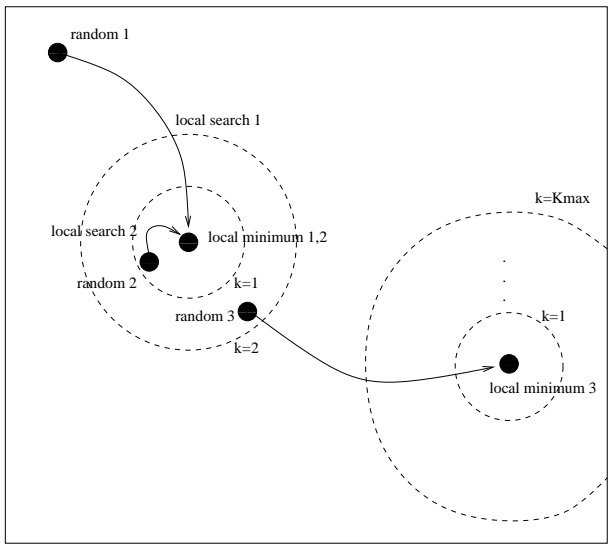


# VNS: Algorithm (sketch)





# VNS: Algorithm (sketch)



# VNS: Configurable parameters

- Maximum neighbourhood size:  $k_{\max}$
- Number of local searches in each neighbourhood  $L$
- Other parameters if further termination conditions included, e.g.:
  - maximum running time
  - desired objective function value
  - ...

# Local Branching

- Efficient heuristic to find good solution for MILPs.
- We consider Local Branching for binary variables [Fischetti and Lodi, 2005]
- Let  $B$  be the set of indices of binary variables, let  $x^*$  be a binary feasible solution, and let  $k \in \mathbb{Z}$ ,  $k > 0$
- We explore the  $k$ -neighbourhood of  $x^*$  by enforcing the local branching constraint:

$$\sum_{i \in B: x_i^* = 1} (1 - x_i) + \sum_{i \in B: x_i^* = 0} x_i \leq k$$

# Branch-and-Bound for cMINLPs

- For convex problems, we can use Branch-and-Bound methods, since obtaining lower bounds is easy
- A typical approach is to relax integrality and solve the resulting convex NLP to optimality
- Branching is done on integer variables
- If the problem is nonconvex, BB can be used as an heuristic (i.e., it finds a local optimum)
- The BB local NLP subsolver needs an initial feasible starting point
- We supply such point computing a constraint feasible (possibly non integral!) solution with an SQP method; this increases our chances of finding an *integer* feasible point

# Sequential Quadratic Programming

- SQP methods find local optima to nonconvex MINLPs
- Idea: solve a sequence of quadratic approximation of the original problem subject to a linearization of the constraints
- The quadratic approximation is obtained by a convex model of the objective function Hessian at a current solution point
- SQP are now at a very advanced stage: there are good chances of finding a constraint feasible point starting from any given initial point, even for large NLPs

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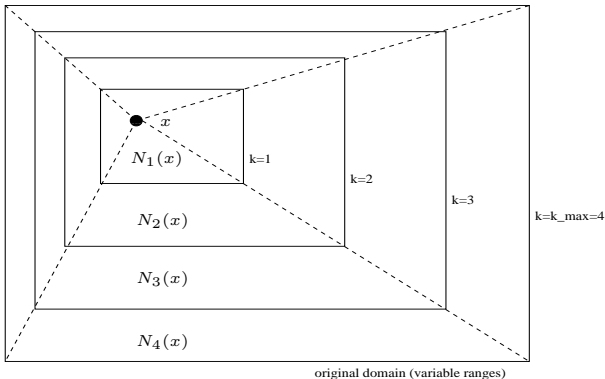
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# The RECIPE algorithm

- We put together all the ingredients into our Relaxed-Exact Continuous-Integer Problem Exploration using a two-phase search
  - ① **Global search**: VNS
  - ② **Local search**: BB method, with initial starting point provided by an SQP method
- Neighbourhood structure:
  - Hyper-rectangular neighbourhoods for continuous and general integer variables
  - Local branching for binary variables (note: the LB constraint is dropped for the SQP search)

# Hyper-rectangular Neighbourhood

- Use hyper-rectangular neighbourhoods  $N_k(x')$  proportional to the region delimited by the variable ranges
- In other words, hyper-rectangular shells of size  $k/k_{\max}$  of the original domain





# Local Branching Neighbourhood

- Hyper-rectangular neighbourhoods are ineffective for binary variables
- Each variable would keep the same value for  $k \leq k_{\max}/2$ , and all variables would be unconstrained for  $k > k_{\max}/2$
- Hence, we use the local branching constraint with a rhs depending on the size of the current neighbourhood  $k$ :

$$\sum_{i \in B: x_i^* = 1} (1 - x_i) + \sum_{i \in B: x_i^* = 0} x_i \leq |B| \frac{k}{k_{\max}}$$

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- Collection of MINLPs, from various sources:
  - Small-scale problems from the literature
  - Large-scale industrial problems
- Provides a common testset for MINLP solvers
- Available at  
<http://www.gamsworld.org/minlp/minlplib.htm>
- The website provides the best known optimum for each instance (and lists the solvers that obtained that value)

- Total number of instances: 265
  - Smallest instance: 1 constraint, 3 variables (2 integer)
  - Largest instance: 24972 constraints, 23827 variables (10920 binary)
- Instances are in GAMS format, but an automatic AMPL reformulator is available
- 20 instances had to be removed due to problems in the reformulation (i.e., unknown or unimplemented operators)  
→ 245 instances

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# Implementation

- VNS: AMPL scripting language [Fourer and Gay, 2002]
- BB solver: `minlp_bb` [Leyffer, 1999]
- SQP solver: `snopt` [Gill, 2006]
- We also used a C program to reformulate the problems with the local branching constraints

# Parameters

- We tested RECIPE on 245 instances of the MINLPLib
- We used the same parameters for all runs:
  - $k_{\max} = 50$
  - $L = 15$
  - Max CPU time: 10 hours
- As we always use the same random seed, we did only one run on each instance

## Results: Feasibility

- Out of 245 instances:
  - 163 putative global optima found (66.3%)
  - 82 with no feasible point found (33.7%)
- Failures were due to both local solvers
  - Several difficult instances where `snopt` does not find any feasible point, or simply fails
  - On small instances, most failures are due to `minlp_bb`, which is unable to attain integrality



## Failures: Statistics

- We compared the average number of variables, constraints, nonzeros, and nonlinear nonzeros, as well as ratio of continuous, binary and integer variables (geometric averages)

	# VARIABLES				# CSTR	NONZEROS	
	TOT	CONT	BIN	INT		TOT	NL
All	73.69	0.487	0.209	0.212	73.22	326.45	50.05
Solved	46.58	0.447	0.237	0.219	41.21	175.41	34.36
Unsolved	218.57	0.588	0.144	0.196	285.18	1441.75	121.84

## Failures: Statistics

- We ran `snopt` on the unsolved instances (i.e. no feasible solution found)
- Out of the 82 instances:
  - Solved<sup>1</sup>: 56
  - Failures: 8
  - Infeasible: 18
- For the instances where no continuous feasible solution is found, the BB solver `minlp_bb` obviously fails

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<sup>1</sup>We include instances where a feasible but not necessarily optimal solution was found

## Results: Optimality

- Out of the 163 instances where RECIPE found a feasible solution:
  - 121 known putative global optima (74.2%)
  - 3 unbounded instances<sup>2</sup> (1.8%)
  - 13 new putative global optima (8.0%)
  - 26 local optima, i.e. a better solution is known (16.0%)
- New optima for the following instances:
  - csched2a: 138 constraints, 233 variables
  - ex3, ex3pb: 32 constraints, 33 variables
  - lop97icx: 88 constraints, 987 variables
  - nuclear14b, nuclear24b: 1786 constraints, 1569 variables
  - nuclear25: 1304 constraints, 1679 variables
  - nuclearvc, nuclearvd, nuclearvf: 318 constraints, 352 variables
  - nvs02, nvs14: 4 constraints, 9 variables

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<sup>2</sup>minlphix, risk2b, risk2bpb

## Results: Optimality

- In total, for 84% of the instances with feasible solution we found an optimum better or equal to the best known
- This corresponds to 55% of the 246 initial instances
- Ranking of methods by number of putative global optima found<sup>3</sup>:
  - ① RECIPE: 55%
  - ② SBB+CONOPT: 37% [Drud, 1985]
  - ③ BARON: 15% [Sahinidis and Tawarmalani, 2005]
  - ④ AlphaECP: 14% [Westerlund and Pörn, 2002]
- Very reliable method, without changing *any* parameter!

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<sup>3</sup>From the GAMS website

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# Conclusions

- Combination of several off-the-shelf components into a reliable MINLP solver
- Global search: straightforward VNS
- Local search: SQP and BB method for convex MINLPs
- Neighbourhood structure: hyper-rectangles and local branching
- Extensive computational testing with hard MINLPs, showing good results

# Future Research: Different Solvers

- Preliminary results show that RECIPE using `ipopt` and `bonmin` is slower, but *significantly* more reliable in terms of feasibility
- Moreover, we do *not* drop the local branching constraint for the SQP search
- The algorithm takes more time, but seems to find better solutions, in particular on the instances with no binary variables

# Future Research: Bound Tightening

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BB for MINLPs

SQP

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## MINLPLib

## Computational Experiments

## Conclusions

- We employ `coutight`, an open-source utility to tighten the variable bounds using expression trees (and more)
- Whenever we define a new neighbourhood, i.e. the local branching constraint changes, we apply the bound tightening phase
- Results are still uncertain: no clear winner



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Conclusions

...and that's all

Thank you!

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