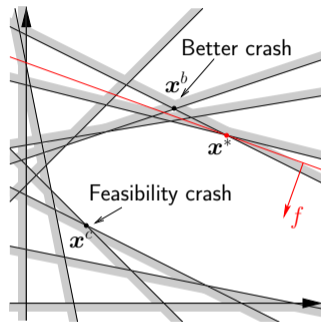


A linear programming problem is

$$\begin{array}{ll} \min & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & A\mathbf{x} = \mathbf{b} \\ & \mathbf{x} \geq \mathbf{0} \end{array}$$



$$\mathbf{x}^0 \xrightarrow{\text{Crash}} \mathbf{x}^k \xrightarrow{\text{Crossover}} \mathbf{x}^b \xrightarrow{\text{Simplex}} \mathbf{x}^*$$

- A good starting basis is essential for the solution of large problems
- The Idiot crash is a heuristic aiming to improve feasibility
- Implemented by John Forrest in CLP
- Seeking primal feasibility prior to primal simplex

$$\mathbf{x}^0 \xrightarrow{\text{Crash}} \mathbf{x}^k \xrightarrow{\text{Crossover}} \mathbf{x}^b \xrightarrow{\text{Simplex}} \mathbf{x}^*$$

Idiot is Augmented Lagrangian

- No documentation but the code
 - John Forrest: "so bad that I called it the Idiot algorithm"
- At each iteration minimize a weighted average of objective and infeasibilities
- Augmented Lagrangian (AL)
- Aspects that make it different from AL
 - Approximate minimization
 - Parameter adjustment
 - Other details

Augmented Lagrangian

- In iteration k

$$\mathbf{x}^{k+1} = \arg \min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} + \sum_{i \in 1..m} \sigma_i^k (r_i(\mathbf{x}^k) + \theta_i^k)^2,$$

- σ_i and θ_i are parameters corresponding to the i^{th} row
- $r_i(\mathbf{x}^k)$ is the residual of the i^{th} row
- Adjust parameters

At start	After some iterations s	After some iterations l
$\sigma^0 = \mathbf{1}$		$\sigma^{l+1} := 10\sigma^l$
$\theta^0 = \mathbf{0}$	$\theta^{s+1} := \theta^s + \mathbf{r}(\mathbf{x}^s)$	$\theta^{l+1} := \theta^l/10$

Alternating directions approach

- Similar to Alternating Direction Method of Multipliers (ADMM)

$$\min_{\mathbf{x}} h(\mathbf{x})$$

$$\min_{x_1} h(\mathbf{x})$$

$$\min_{x_2} h(\mathbf{x})$$

$$\min_{x_3} h(\mathbf{x})$$

...

$$\min_{x_n} h(\mathbf{x})$$

- Approximate solution
- repeated ≈ 100 times to improve accuracy

The Idiot Crash structure

Initialize \mathbf{x}^0 , σ^0 , $\theta^0 = \mathbf{0}$

For $l \in 1..nMajor$

For $i \in 1..nMinor$

$$\forall j \in \{1..n\} \quad \min_{x_j} \quad \mathbf{c}^T \mathbf{x} + \sum_{i \in 1..m} \sigma^k (r_i(\mathbf{x}^k) + \theta_i^k)^2$$

end

Choose new σ or θ

end

- $\sigma^k = \sigma_1^k = \sigma_2^k = \dots = \sigma_m^k$
- $\theta_i^{s+1} := \frac{1}{2} r_i(\mathbf{x}^s)$

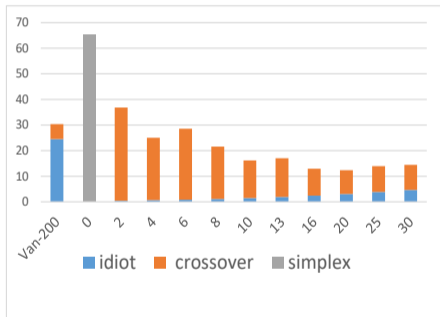
At the end of each major iteration the values of θ or σ are re-adjusted:

- Start with σ^0 , $\theta^0 = \mathbf{0}$, nMinor = 2
- At the end of each major iteration:
 - Until 10% reduction in primal infeasibility set $\sigma^{k+1} = 10\sigma^k$
- Set nMinor = 105
 - The first major iteration with a new σ , θ is unchanged
 - The next few major iterations set $\theta_i^{k+1} = \frac{1}{2}r_i(\mathbf{x}^k)$
 - Increase σ and repeat

- Generally useless
 - Single variable change limitation
- Solves Quadratic Assignment Problems (QAPs)
 - Combinatorial optimization problem, special case of facility location
 - Well known for being hard to solve
 - The Idiot crash reduces solution time significantly

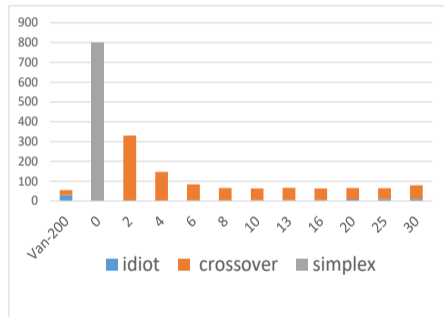
Quadratic Assignment Problems

QAP12
Solution time (s)



nMajor

QAP15
Solution time (s)



nMajor

$$\begin{aligned} \min \quad & f_P = \mathbf{c}^T \mathbf{x} \\ \text{s.t.} \quad & A\mathbf{x} = \mathbf{b} \\ & \mathbf{x} \geq \mathbf{0} \end{aligned} \quad (\text{P})$$

$$\begin{aligned} \max \quad & f_D = \mathbf{b}^T \mathbf{y} \\ \text{s.t.} \quad & A^T \mathbf{y} \leq \mathbf{c} \end{aligned} \quad (\text{D})$$

Idiot applied to (P)

- Primal feasible
- Near-optimal objective
 $f_P \geq f^*$

Idiot applied to (D)

- Dual feasible
- Objective $f_D \leq f^*$

Problem	LB	UB	f^*	Time (s)		
				Bounds	Idiot+Crossover	Simplex
qap08	141.39	204.57	203.50	0.55	0.61	1.80
qap12	481.50	523.60	522.89	3.85	12.64	65.21
qap15	950.05	1042.05	1040.99	11.53	64.48	803.30

- QAPs require integer solution to linearization
- Fast bounds on f^* accelerate branch & bound algorithms