A quadratic penalty algorithm for linear programming and its application to linearizations of quadratic assignment problems

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Computational Optimization in Action

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THE UNIVERSITY of EDINBURGH

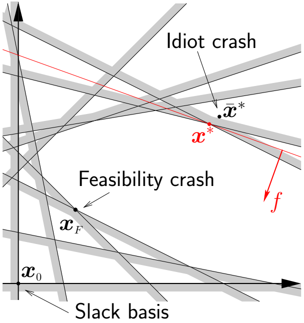
Google

Solving LP problems: Crash start

$$\text{minimize} \quad f = \boldsymbol{c}^T\boldsymbol{x} \qquad \text{subject to} \quad A\boldsymbol{x} \leq \boldsymbol{b} \qquad \boldsymbol{x} \geq \boldsymbol{0}$$

Choosing the initial basis

- **“Slack” basis** is simple choice $\boldsymbol{x}_0$
- Standard **crash** aims for feasible vertex $\boldsymbol{x}_F$
- **“Idiot” crash** aims for near-optimal point $\bar{\boldsymbol{x}}^*$



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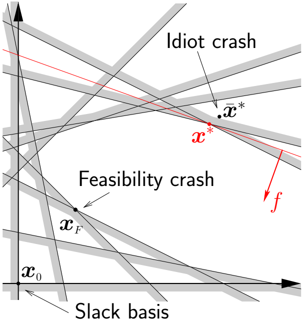
  - (Why) does it work?
  - How good is it?



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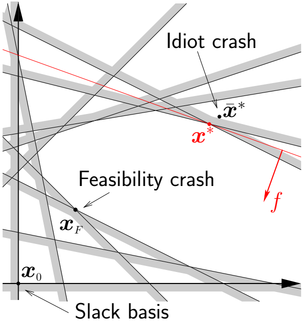

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  - What is it?
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- **Analysis:** Forrest (2014)
  - "For many problems you finish with a small sum of infeasibilities and an objective a bit higher than the optimal one"

Idiot crash: Sounds familiar?

$$\text{minimize} \quad f(\boldsymbol{x}) \qquad \text{subject to} \quad \boldsymbol{r}(\boldsymbol{x}) = \boldsymbol{0}$$

Quadratic penalty method

- Minimize
  $\phi(\boldsymbol{x}, \mu) = f(\boldsymbol{x}) + \frac{1}{2\mu}\boldsymbol{r}(\boldsymbol{x})^T\boldsymbol{r}(\boldsymbol{x})$
- Decreasing sequence $\{\mu^k\}$
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  - $\boldsymbol{\lambda}_i^{k+1} = \boldsymbol{\lambda}_i^k + \mu^k\boldsymbol{r}(\boldsymbol{x}^k)$
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Idiot algorithm

- Starts like augmented Lagrangian
- Finishes like quadratic penalty method

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The Idiot algorithm: $\boldsymbol{r}(\boldsymbol{x}) = A\boldsymbol{x} - \boldsymbol{b}$

Initialize $\boldsymbol{x}^0 \geq \boldsymbol{0}$, μ^1, $\boldsymbol{\lambda}^1 = \boldsymbol{0}$

For $k = 1, 2, 3, \ldots K$

$$\boldsymbol{x}^k = \arg\min_{\boldsymbol{x}\geq\boldsymbol{0}} h(\boldsymbol{x}) = \boldsymbol{c}^T\boldsymbol{x} + {\boldsymbol{\lambda}^k}^T\boldsymbol{r}(\boldsymbol{x}) + \frac{1}{2\mu^k}\boldsymbol{r}(\boldsymbol{x})^T\boldsymbol{r}(\boldsymbol{x})$$

Possibly update μ:

$\mu^{k+1} = \mu^k/\omega$, for some factor $\omega > 1$

$\boldsymbol{\lambda}^{k+1} = \boldsymbol{\lambda}^k$

Else update $\boldsymbol{\lambda}$:

$\mu^{k+1} = \mu^k$

$\boldsymbol{\lambda}^{k+1} = \mu^k\boldsymbol{r}(\boldsymbol{x}^k)$

End

Idiot crash: Algorithm

- Solve subproblem

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- Initially
  - Penalty parameter μ^1 ranges between 0.001 and 1000
  - Perform 20-30 “sample iterations”, minimizing component-wise twice
  - Possibly abandon Idiot if 10% primal infeasibility reduction not achieved

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  - Number of iterations K ranges between 30 and 200
  - μ is reduced (every 3 or 6 iterations) by $\omega = 0.333$ (typically)
- Final value of μ is around machine precision
- $\boldsymbol{\lambda}^k \rightarrow \boldsymbol{0}$ rapidly

Idiot crash: How effective is it?

Results: Speed-up of the `clp` primal simplex solver when the Idiot crash is used and the percentage of solution time accounted for by the Idiot crash

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Best			Worst		
Model[1]	Speed-up	Idiot (%)	Model[1]	Speed-up	Idiot (%)
Linf_520c	9.4	8.2	FOME12	1.1	0.1
STP3D	6.5	0.9	KEN-18	1.0	0.7
self	6.1	22.7	DFL001	1.0	0.1
STORM_1000	4.5	0.8	PDS-80	1.0	0.1
nug15	4.2	0.1	**maros-r7**	0.9	7.8
STORM-125	4.1	10.1	TRUSS	0.8	17.1

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- Mean speed-up is 1.9; mean solution time accounted for by Idiot is 6%
- For only **some problems** does vanilla clp use the Idiot crash and primal simplex

[1: Results drawn from experiments on 30 Mittelmann benchmarking problems]

Idiot crash: Effect on `clp` benchmark performance

Results: Performance of `clp` relative to `cplex`, `gurobi` and `xpress`

Mittelmann (25/04/18)

Model	`cplex`	`gurobi`	`xpress`	`clp`
LINF_520C	495	574	255	35
NUG15	338	12	7	14
QAP12	26	1	1	5
QAP15	365	12	6	13
SELF	18	12	15	5

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- For LINF_520C, clp is vastly faster
- For the three QAP linearizations, clp is very much faster than cplex
- For SELF, clp is significantly faster

Idiot crash: Can it solve LPs?

Results: Accuracy of final point after (up to) 200 Idiot iterations

- Residual $\|A\boldsymbol{x} - \boldsymbol{b}\|_2$
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Model	Residual	Objective	Model	Residual	Objective
NUG15	2.1×10^{-10}	3.7×10^{-4}	DBIC1	3.8×10^{-1}	8.5×10^{-2}
MAROS-R7	4.0×10^{-9}	2.3×10^{-5}	STORM-125	1.4×10^{0}	1.2×10^{-1}
PDS-100	7.6×10^{-10}	3.7×10^{-4}	TRUSS	7.1×10^{-1}	3.2×10^{-1}
QAP15	2.1×10^{-10}	2.8×10^{-3}	MOD2	3.9×10^{0}	2.1×10^{-1}
LP22	1.1×10^{-9}	1.3×10^{-3}	PILOT87	2.1×10^{0}	6.8×10^{-1}
DFL001	1.1×10^{-9}	3.7×10^{-3}	WORLD	4.3×10^{0}	5.5×10^{-1}

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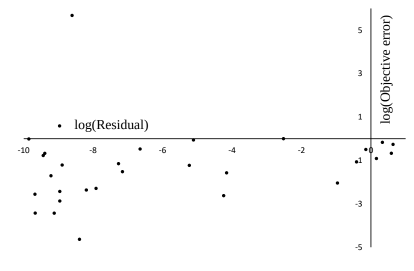
- Idiot crash clearly solves some problems to acceptable tolerances
- Objective error measure using f^* is not an optimality test

Idiot crash: For what LPs does it work well?

Accuracy measure



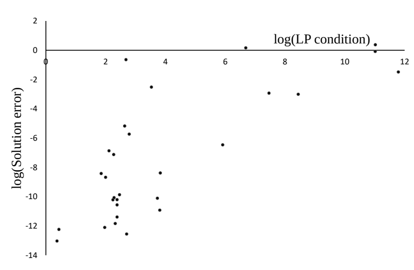
A convenient single quality measure for the point returned by the Idiot crash is

$$\text{qual}(\boldsymbol{x}) = \|A\boldsymbol{x} - \boldsymbol{b}\| \times \frac{|f - f^*|}{\max(1, |f^*|)}$$

No problems with low value of qual($\boldsymbol{x}$) have accurate optimal objective function value but large residual

Idiot crash: For what LPs does it work well?

Accuracy and condition



- Clear correlation between accuracy of final point and cond(A)
- Quadratic assignment problems are particularly well conditioned

Idiot crash: What can be proved?

$$\text{minimize} \quad f = \boldsymbol{c}^T\boldsymbol{x} \qquad \text{subject to} \quad A\boldsymbol{x} = \boldsymbol{b} \qquad \boldsymbol{x} \geq \boldsymbol{0}$$

The Idiot objective is bounded below for bounded LP problems

The Idiot objective $h^k(\boldsymbol{x}) = \boldsymbol{c}^T\boldsymbol{x} + {\boldsymbol{\lambda}^k}^T\boldsymbol{r}(\boldsymbol{x}) + \dfrac{1}{2\mu^k}\boldsymbol{r}(\boldsymbol{x})^T\boldsymbol{r}(\boldsymbol{x})$, where $\boldsymbol{r}(\boldsymbol{x}) = A\boldsymbol{x} - \boldsymbol{b}$, has positive semi-definite Hessian A^TA, but unboundedness of $h^k(\boldsymbol{x})$ implies unboundedness of the LP

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The Idiot algorithm with exact solution of subproblems converges

Theorem: Suppose, that $\boldsymbol{x}^k$ is the exact global minimizer of $h^k(\boldsymbol{x})$ for each $k = 1, 2\ldots$ and that $\{\mu^k\} \rightarrow 0$ as $k \rightarrow \infty$. Then every limit point of the sequence $\{\boldsymbol{x}^k\}$ is a solution to the LP problem.

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However: Subproblems are not (currently) solved exactly and ill-conditioning due to small μ mitigates against it

Idiot crash: What happens next?

- Final point is *not* a vertex (basic) solution
- `clp` performs
  - **Crossover** to get a basic solution
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LINF_520C	9.4	8.2	1.1×10^{-1}	9.1×10^{-3}

Idiot is a worthwhile crash, but relatively expensive to establish optimality!

Idiot crash: Bounding the optimal objective value

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$$\text{maximize} \quad f_D = \boldsymbol{b}^T \boldsymbol{y} \qquad \text{subject to} \quad A^T \boldsymbol{y} + \boldsymbol{s} = \boldsymbol{c} \qquad \boldsymbol{s} \geq \boldsymbol{0}$$

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- **Unfortunately:** Values of $\bar{f}_D^*$ don't (yet) have high accuracy

Idiot crash: Application to quadratic assignment problem linearizations

Quadratic assignment problem (QAP)

$$\min\ f(X) = \sum_{i,j,k,l} a_{ik} b_{jl} x_{ij} x_{kl} \quad \text{s.t. } X = [x_{ij}]_{n\times n} \in \Pi_n$$

This is a MIQP problem with n^2 binary variables and $2n$ constraints

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QAP linearization (Adams and Johnson)

$$\begin{aligned}
\min \quad & f(X) = \sum_{i,j,k,l} a_{ik} b_{jl} y_{ijkl} \\
\text{s.t.} \quad & \sum_{i} y_{ijkl} = x_{kl},\ \ j,k,l = 1,\ldots,n; \quad \sum_{j} y_{ijkl} = x_{kl},\ \ i,k,l = 1,\ldots,n \\
& y_{ijkl} \geq 0,\ \ i,j,k,l = 1,\ldots,n; \quad X = [x_{ij}]_{n\times n} \in \Pi_n
\end{aligned}$$

This is a MILP problem with n^2 binary variables; n^4 continuous variables $y_{ijkl} = x_{ij}x_{kl}$ and $n^4 + 2n^3 + 2n$ constraints.

Idiot crash: Application to quadratic assignment problem linearizations

Results: Performance after (up to) 200 Idiot iterations

Model	Rows	Columns	Optimum	Residual	Objective	Error	Time
NUG05	210	225	50.00	9.4×10^{-9}	50.01	1.5×10^{-4}	0.04
NUG06	372	486	86.00	7.8×10^{-9}	86.01	1.2×10^{-4}	0.11
NUG07	602	931	148.00	7.9×10^{-9}	148.64	4.3×10^{-3}	0.25
NUG08	912	1613	203.50	7.0×10^{-9}	204.41	4.5×10^{-3}	0.47
NUG12	3192	8856	522.89	8.8×10^{-9}	523.86	1.8×10^{-3}	2.58
NUG15	6330	22275	1041.00	8.9×10^{-9}	1041.38	3.7×10^{-4}	5.13
NUG20	15240	72600	2182.00	7.5×10^{-9}	2183.03	4.7×10^{-4}	14.94
NUG30	52260	379350	4805.00	1.1×10^{-8}	4811.41	1.3×10^{-3}	82.28

- Solution of NUG30 intractable using simplex or IPM on the same machine
- Idiot crash consistently yields near-optimal solutions
- Useful within a branch-and-bound solver?

Idiot crash: Future work

Exact Idiot

- Convergence of component-wise search can be prohibitively slow
- Solve
$$\min_{\boldsymbol{x}\geq\boldsymbol{0}} h(\boldsymbol{x}) = \boldsymbol{c}^T\boldsymbol{x} + {\boldsymbol{\lambda}^k}^T\boldsymbol{r}(\boldsymbol{x}) + \frac{1}{2\mu^k}\boldsymbol{r}(\boldsymbol{x})^T\boldsymbol{r}(\boldsymbol{x})$$
directly using conjugate gradient based approach
- Preconditioning?

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Parallel Idiot

- Approximate or exact Idiot dominated by cost of forming $A\boldsymbol{x}$
- "Obvious" parallelism is memory bound
- Problem-specific code?

Conclusions on the Idiot crash

- Has been presented in algorithmic form for the first time
- Generally beneficial for the primal revised simplex method
- Converges to an optimal solution when subproblems are solved exactly
- Consistently and quickly yields near-optimal solutions of QAP linearizations intractable with simplex or IMP

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Slides: http://www.maths.ed.ac.uk/hall/COA18

Report: http://www.maths.ed.ac.uk/hall/GaHa18