

# Algorithm NCL

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## Abstract

Optimization problems  $\min \phi(x)$  st  $c(x) \geq 0$  may have LICQ difficulties. We extend the BCL and LCL approaches of LANCELOT and MINOS to Algorithm NCL, whose subproblems optimize an augmented Lagrangian subject to constraints that satisfy LICQ:

$$\min_{x,r} \phi(x) + y_k^T r + \frac{1}{2} \rho_k \|r\|^2 \text{ st } c(x) + r \geq 0.$$

The variables  $r$  lead to many superbasic variables with active-set solvers like MINOS and SNOPT, but are easily accommodated by interior methods. We illustrate with Taxation Policy problems modeled in AMPL. Algorithm NCL converges in about 10 major iterations (independent of problem size), and IPOPT is able to warm-start each major iteration.

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# The NLP problem

# The NLP problem

NCO

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} \quad \phi(x)$$

$$\text{subject to } c(x) \geq 0, \quad Ax \geq b, \quad \ell \leq x \leq u$$

- $\phi(x)$  is a smooth nonlinear function
- $c(x) \in \mathbb{R}^m$  is a vector of smooth nonlinear functions
- General linear constraints and bounds
- Many inequalities  $c(x) \geq 0$  might not satisfy LICQ at  $x^*$

Example:  $m = 571,000, \quad n = 1500, \quad A: 1 \times n$   
10,000 constraints essentially active:  $c_i(x^*) \leq 10^{-6}$

BCL

LCL

NCL

**Sequence of subproblems minimizing  
X-constrained (augmented) Lagrangian**

**BCL** LANCELOT (1992)

**LCL** Robinson (1972)

MINOS (1982)

**sLCL** KNOSSOS (2002)

**NCL** Ma, Judd, Orban & S (2017)

Different implementation of **BCL!**  
**(AMPL loop + IPOPT)**

# LANCELOT's BCL algorithm for general NLP

# LANCEROT

Equality constraints:

$$\min \phi(x) \text{ st } c(x) = 0, \ell \leq x \leq u$$

**BCL subproblems:**

$$\begin{aligned} \text{BC}_k \quad & \underset{x}{\text{minimize}} \quad L(x, y_k, \rho_k) = \phi(x) - y_k^T c(x) + \frac{1}{2} \rho_k \|c(x)\|^2 \\ & \text{subject to } \ell \leq x \leq u \end{aligned}$$

$y_k$  estimates dual variables,  $\rho_k$  penalty parameter

Loop:

- solve  $\text{BC}_k$  to get  $x_k^*$  decreasing opttol  $\omega_k$
- if  $\|c(x_k^*)\| \leq \eta_k$ ,  $y_{k+1} \leftarrow y_k - \rho_k c(x_k^*)$  decreasing featol  $\eta_k$
- else  $\rho_{k+1} \leftarrow 10\rho_k$

# Algorithm NCL for general NLP

## NCL subproblems

$c(x) \geq 0$  as equalities:

$$\begin{aligned} \text{NCO}' \quad & \underset{x, s}{\text{minimize}} \quad \phi(x) \\ & \text{subject to } c(x) - s = 0, \quad Ax \geq b, \quad \ell \leq x \leq u, \quad s \geq 0 \end{aligned}$$

## NCL subproblems

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LANCELOT subproblems:

$$\begin{aligned} \text{BC}_k' \quad & \underset{x, s}{\text{minimize}} \quad L(x, \mathbf{y}_k, \rho_k) = \phi(x) - \mathbf{y}_k^T(c(x) - s) + \frac{1}{2}\rho_k \|c(x) - s\|^2 \\ & \text{subject to } Ax \geq b, \quad \ell \leq x \leq u, \quad s \geq 0 \end{aligned}$$

## NCL subproblems

$c(x) \geq 0$  as equalities:

$$\begin{aligned} \text{NCO}' \quad & \underset{x, s}{\text{minimize}} \quad \phi(x) \\ & \text{subject to } c(x) - s = 0, \quad Ax \geq b, \quad \ell \leq x \leq u, \quad s \geq 0 \end{aligned}$$

LANCELOT subproblems:

$$\begin{aligned} \text{BC}_k' \quad & \underset{x, s}{\text{minimize}} \quad L(x, \mathbf{y}_k, \rho_k) = \phi(x) - \mathbf{y}_k^T(c(x) - s) + \frac{1}{2}\rho_k \|c(x) - s\|^2 \\ & \text{subject to } Ax \geq b, \quad \ell \leq x \leq u, \quad s \geq 0 \end{aligned}$$

Introduce  $\mathbf{r} = -(c(x) - s)$ :

$$\begin{aligned} \text{NC}_k \quad & \underset{x, \mathbf{r}}{\text{minimize}} \quad \phi(x) + \mathbf{y}_k^T \mathbf{r} + \frac{1}{2}\rho_k \|\mathbf{r}\|^2 \\ & \text{subject to } c(x) + \mathbf{r} \geq 0, \quad Ax \geq b, \quad \ell \leq x \leq u \end{aligned}$$

Free vars  $\mathbf{r}$  make the nonlinear constraints independent and feasible IPOPT is happy!

# Optimal Tax Policy

## Optimal tax policy

TAX	$\text{maximize}_{c, y}$	$\sum_i \lambda_i U^i(c_i, y_i)$
	subject to	$U^i(c_i, y_i) - U^i(c_j, y_j) \geq 0 \quad \text{for all } i, j$
		$\lambda^T(y - c) \geq 0$
		$c, y \geq 0,$

where  $c_i$  and  $y_i$  are the consumption and income of taxpayer  $i$ , and  $\lambda$  is a vector of positive weights. The utility functions  $U^i(c_i, y_i)$  are each of the form

$$U(c, y) = \frac{(c - \alpha)^{1-1/\gamma}}{1 - 1/\gamma} - \psi \frac{(y/w)^{1/\eta+1}}{1/\eta + 1},$$

where  $w$  is the wage rate and  $\alpha, \gamma, \psi$  and  $\eta$  are taxpayer heterogeneities.

## Optimal tax policy

More precisely,

$$U^{i,j,k,g,h}(c_{p,q,r,s,t}, y_{p,q,r,s,t}) = \frac{(c_{p,q,r,s,t} - \alpha_k)^{1-1/\gamma_h}}{1 - 1/\gamma_h} - \psi_g \frac{(y_{p,q,r,s,t}/w_i)^{1/\eta_j + 1}}{1/\eta_j + 1},$$

where  $(i, j, k, g, h)$  and  $(p, q, r, s, t)$  run over 5 dimensions:

<i>na</i>	wage types	= 5
<i>nb</i>	elasticities of labor supply	= 3
<i>nc</i>	basic need types	= 3
<i>nd</i>	levels of distaste for work	= 2
<i>ne</i>	elasticities of demand for consumption	= 2

$T =$	$na \times nb \times nc \times nd \times ne$	= 180
$m =$	$T(T - 1)$ nonlinear constraints	= 32220
$n =$	$2T$ variables	= 360

## AMPL model

TAX	$\text{maximize}_{c, y} \quad \sum_i \lambda_i U^i(c_i, y_i)$ $\text{subject to} \quad U^i(c_i, y_i) - U^i(c_j, y_j) \geq 0 \quad \text{for all } i, j$ $\lambda^T(y - c) \geq 0$ $c, y \geq 0,$
-----	--

```
Incentive{(i,j,k,g,h) in T, (p,q,r,s,t) in T:
  !(i=p and j=q and k=r and g=s and h=t)}:
  (c[i,j,k,g,h] - alpha[k])^(1-1/gamma[h]) / (1-1/gamma[h])
  - psi[g]*(y[i,j,k,g,h]/w[i])^mu1[j] / mu1[j]
  - (c[p,q,r,s,t] - alpha[k])^(1-1/gamma[h]) / (1-1/gamma[h])
  + psi[g]*(y[p,q,r,s,t]/w[i])^mu1[j] / mu1[j]
  >= 0;
```

Technology:

```
sum{(i,j,k,g,h) in T} lambda[i,j,k,g,h]*(y[i,j,k,g,h] - c[i,j,k,g,h]) >= 0;
```

## Piecewise-smooth extension

```
Incentive{(i,j,k,g,h) in T, (p,q,r,s,t) in T:  
    !(i=p and j=q and k=r and g=s and h=t)}:  
    (if c[i,j,k,g,h] - alpha[k] >= epsilon then  
        (c[i,j,k,g,h] - alpha[k])^(1-1/gamma[h]) / (1-1/gamma[h])  
        - psi[g]*(y[i,j,k,g,h]/w[i])^mu1[j] / mu1[j]  
    else  
        - 0.5/gamma[h] *epsilon^(-1/gamma[h]-1)*(c[i,j,k,g,h] - alpha[k])^2  
        + (1+1/gamma[h])*epsilon^(-1/gamma[h])*(c[i,j,k,g,h] - alpha[k])  
        + (1/(1-1/gamma[h]) - 1 - 0.5/gamma[h])*epsilon^(1-1/gamma[h])  
        - psi[g]*(y[i,j,k,g,h]/w[i])^mu1[j] / mu1[j]  
    )  
    - (if c[p,q,r,s,t] - alpha[k] >= epsilon then  
        ...  
    ) >= 0;
```

# SNOPT on problem TAX

$na, nb, nc, nd, ne = 5, 3, 3, 2, 2 \quad m = 32220 \quad n = 360$

	Total	Normal	Free	Fixed	Bounded
Rows	32222	32221	1	0	0
Columns	360	0	0	0	360

No. of matrix elements	129600	Density	1.117
Biggest	1.0000E+00	(excluding fixed columns,	
Smallest	0.0000E+00	free rows, and RHS)	

Nonlinear constraints	32220	Linear constraints	2
Nonlinear variables	360	Linear variables	0
Jacobian variables	360	Objective variables	360
Total constraints	32222	Total variables	360

# SNOPT on problem TAX

Major	Minors	Step	nCon	Feasible	Optimal	MeritFunction	nS	condHz	Penalty	r	t
0	866		1	(3.7E-15)	4.9E-04	4.1745522E+02	4	4.1E+08	1.0E+04	_	t
1	503	2.7E-02	6	(3.6E-15)	6.5E-02	4.1746922E+02	24	3.2E+05	1.0E+04	_n	r
2	134	1.0E-01	11	(1.4E-07)	2.7E-05	4.1755749E+02	8	2.6E+09	1.8E+06	_s	
3	313	9.8E-02	16	(1.4E-07)	8.9E-05	4.1764438E+02	43	1.0E+07	1.8E+06	_	
4	153	2.8E-02	21	(5.5E-08)	1.8E-04	4.1767129E+02	35	2.2E+04	1.8E+06	_	
5	103	2.2E-02	26	(5.4E-08)	9.5E-04	4.1769616E+02	34	6.7E+07	1.8E+06	_	
6	87	2.1E-02	31	(5.3E-08)	1.2E-03	4.1772079E+02	32	1.6E+08	1.8E+06	_	
7	161	7.3E-03	35	(5.2E-08)	9.7E-04	4.1772930E+02	31	2.4E+05	1.8E+06	_	
8	64	7.3E-03	39	(5.2E-08)	1.1E-03	4.1773783E+02	33	9.7E+05	1.8E+06	_	
9	83	7.2E-03	43	(5.2E-08)	1.2E-03	4.1774637E+02	37	1.9E+07	1.8E+06	_	
10	72	7.2E-03	47	(5.1E-08)	9.9E-04	4.1775484E+02	31	1.3E+08	1.8E+06	_	
99	154	7.2E-03	459	(1.0E-08)	2.7E-05	4.1839776E+02	32	7.9E+06	1.8E+06	_	
100	343	7.2E-03	463	(1.0E-08)	4.9E-03	4.1839867E+02	50	4.3E+07	1.8E+06	_	R
106	413	7.3E-03	496	(1.0E-08)	1.8E-05	4.1840397E+02	17	5.0E+07	1.8E+06	_	
107	630	7.2E-03	500	(1.0E-08)	1.4E-01	1.5496435E+06	6	1.0E+12	1.8E+06	_	it

# SNOPT on problem TAX

Major	Minors	Step	nCon	Feasible	Optimal	MeritFunction	nS	condHz	Penalty		
108	503	5.1E-02	503	(1.0E-08)	3.7E-02	1.2973689E+06	12	2.2E+04	1.8E+06	_	m
109	1805	4.0E-01	506	1.3E-05	7.5E-01	2.3393279E+05	9	4.8E+04	1.8E+06	_	it
110	16517	2.0E-01	509	1.1E-05	1.0E+00	2.6854996E+05	2	7.5E+03	1.8E+06	_	it
117	175544	1.0E+00	526	1.0E-04	1.0E+00	1.0282166E+09	13	7.6E+07	1.8E+06	_	mr it
118	1681	1.0E+00	528	3.0E-04	1.0E+00	1.7677788E+10	23	1.7E+09	2.9E+06	_smr	it
119	919	1.0E+00	530	2.0E-05	2.4E-02	8.1274014E+07	39	1.1E+06	3.0E+07	_sm	t
194	30811	1.0E+00	795	8.6E-01	9.7E-01	2.8330244E+21	2	1.8E+01	3.5E+13	_n	it
195	1819	1.1E-04	800	8.6E-01	1.0E+00	2.6326936E+22	3	1.4E+02	1.1E+15	_n R	it
195	3314		800	8.6E-01	1.0E+00	2.8661156E+22			1.0E+04	_n r	it
195	4439		800	8.6E-01	9.9E-01	2.8661156E+22			1.0E+04	_n r	it

SNOPTB EXIT 40 -- terminated after numerical difficulties

SNOPTB INFO 41 -- current point cannot be improved

# IPOPT on problem TAX

$na, nb, nc, nd, ne = 5, 3, 3, 2, 2 \quad m = 32220 \quad n = 360$

This is Ipopt version 3.12.4, running with linear solver mumps.

NOTE: Other linear solvers might be more efficient (see Ipopt documentation).

Number of nonzeros in inequality constraint Jacobian.: 129240

Number of nonzeros in Lagrangian Hessian.....: 360

Total number of variables.....: 360

variables with only lower bounds: 360

Total number of inequality constraints.....: 32221

inequality constraints with only lower bounds: 32221

# IPOPT on problem TAX

iter	objective	inf_pr	inf_du	lg(mu)	d	lg(rg)	alpha_du	alpha_pr	ls
0	-4.1745522e+02	0.00e+00	2.52e+00	-1.0	0.00e+00	-	0.00e+00	0.00e+00	0
1	-4.1734473e+02	6.18e-03	7.36e+00	-1.0	1.34e+00	-	7.69e-01	2.05e-01f	1
2	-4.1682694e+02	4.93e-03	1.78e+01	-1.0	5.48e+00	-	2.23e-01	1.34e-01f	1
3	-4.1656532e+02	4.60e-03	1.66e+02	-1.0	6.95e+00	-	3.06e-01	5.29e-02f	1
4	-4.1553526e+02	3.69e-03	2.13e+02	-1.0	9.40e+00	-	2.38e-01	1.60e-01f	1
5	-4.1470856e+02	3.45e-03	2.96e+02	-1.0	1.14e+01	-	1.65e-01	1.17e-01f	1
6	-4.1433731e+02	3.72e-03	9.79e+02	-1.0	1.30e+01	-	1.73e-01	5.83e-02f	1
7	-4.1433774e+02	3.53e-03	5.22e+03	-1.0	2.47e-02	2.0	5.60e-01	5.64e-02h	1
8	-4.1433988e+02	3.09e-03	5.10e+04	-1.0	3.46e-01	1.5	1.00e+00	1.24e-01h	1
9	-4.1434074e+02	2.15e-03	2.87e+04	-1.0	3.40e-01	1.0	5.03e-01	3.01e-01h	1
10	-4.1428766e+02	1.22e-03	1.50e+04	-1.0	3.01e-01	0.6	4.75e-01	5.39e-01h	1
11	-4.1429091e+02	1.05e-03	1.27e+04	-1.0	2.21e-01	1.0	3.87e-01	1.24e-01h	1
77	-4.0990702e+02	0.00e+00	4.57e-02	-1.0	6.32e-03	-	1.00e+00	1.00e+00h	1
78	-4.0995159e+02	0.00e+00	5.00e+04	-2.5	4.68e+00	-	9.27e-01	1.00e+00f	1

# IPOPT on problem TAX

iter	objective	inf_pr	inf_du	lg(mu)	d	lg(rg)	alpha_du	alpha_pr	ls
88	-4.1227845e+02	0.00e+00	4.45e-03	-2.5	2.55e+00	-	1.00e+00	1.00e+00h	1
89	-4.1320008e+02	2.97e-03	8.22e+02	-3.8	6.90e+01	-	2.57e-01	4.28e-01f	1
160	-4.1641067e+02	0.00e+00	1.50e-03	-3.8	1.25e-01	-	1.00e+00	1.00e+00f	1
161	-4.1646520e+02	8.99e-06	9.47e+00	-5.7	4.36e+00	-	2.62e-01	2.63e-01f	1
384	-4.1702347e+02	4.14e-07	3.89e+09	-5.7	4.11e-03	0.6	2.59e-01	1.15e-01f	1
385r	-4.1702347e+02	4.14e-07	1.00e+03	-5.4	0.00e+00	4.6	0.00e+00	2.07e-07R	2
419r	-4.1580769e+02	0.00e+00	9.69e-06	-5.4	2.10e-02	-	1.00e+00	1.00e+00h	1
420r	-4.1589722e+02	9.33e-07	2.86e+02	-8.1	1.29e+01	-	1.62e-01	3.97e-01f	1
449r	-4.1630403e+02	1.13e-05	2.79e-05	-8.1	2.92e-01	-	1.00e+00	9.77e-01h	1

	(scaled)	(unscaled)
Objective.....	-4.1630466137535933e+02	-4.1630466137535933e+02
Dual infeasibility.....	1.1130803588695777e+00	1.1130803588695777e+00
Constraint violation....	0.0000000000000000e+00	0.0000000000000000e+00
Complementarity.....	1.3412941119075164e-08	1.3412941119075164e-08
Total CPU secs in IPOPT (w/o function evaluations)	=	151.4
Total CPU secs in NLP function evaluations	=	65.6

# LANCERLOT on problem TAX

$na, nb, nc, nd, ne = 5, 3, 3, 2, 2 \quad m = 32220 \quad n = 360$

k	muk	omegak	etak	Obj	itns	CGit	TRradius	active
1	1.0e-1	1.0e-1	1.0e-1	-417.455	18	12000	4.1e-01	2831
2	1.0e-1	1.0e-2	1.2e-2	-421.606	39	9000	1.6e-01	2568
3	1.0e-2	1.0e-2	7.9e-2	-421.011	23	11000	2.4e-01	1662
4	1.0e-2	1.0e-4	1.3e-3	-420.188	282	104000	8.6e-02	1444
5	1.0e-3	1.0e-3	6.3e-2	-419.967	134	64000	5.7e-02	1004
6	1.0e-3	1.0e-6	1.3e-4	-419.819	198	156000	3.1e-02	901
7	1.0e-4	1.0e-4	5.0e-2	-419.741	300	308000	3.1e-12	710
8	1.0e-4	1.0e-6	1.3e-5	-419.698	327	623000	5.5e-04	709
9	1.0e-5	1.0e-5	4.0e-2	-419.682	253	724000	4.7e-03	653
10	1.0e-5	1.0e-6	1.3e-6	-419.676	154	1031000	4.2e-11	663
11	1.0e-6	1.0e-6	3.2e-2	...				

1970 iterations, 8 hours CPU on NEOS

# AMPL implementation of NCL

## pTax5Dnclipopt.run

```
reset; model pTax5Dinitial.run;

reset; model pTax5Dncl.mod;
data pTax5Dncl.dat;
data; var include p5Dinitial.dat;

model; option solver ipopt;
option show_stats 1;
option ipopt_options 'dual_inf_tol=1e-6 max_iter=5000';
```

## pTax5Dnclipopt.run

```
for {K in 1..kmax}
{  if K == 2 then {option ipopt_options $ipopt_options
                      ' warm_start_init_point=yes   mu_init=1e-4'};
  if K == 4 then {option ipopt_options $ipopt_options ' mu_init=1e-5'};
  if K == 6 then {option ipopt_options $ipopt_options ' mu_init=1e-6'};
  if K == 8 then {option ipopt_options $ipopt_options ' mu_init=1e-7'};
  if K ==10 then {option ipopt_options $ipopt_options ' mu_init=1e-8'};

solve;

let rmax := max({(i,j,k,g,h) in T, (p,q,r,s,t) in T:
  !(i=p and j=q and k=r and g=s and h=t)} R[i,j,k,g,h,p,q,r,s,t]);
let rmin := ...
let rnrm := max(abs(rmax), abs(rmin));  # ||r||_inf
if rnrm <= rtol then { printf "Stopping: rnrm is small\n"; break; }
```

## pTax5Dnclipopt.run

```

if ||rk*|| ≤ ηk, yk+1 ← yk + ρkrk*

if rnorm <= etak then    # update dual estimate dk; save new solution
{let {(i,j,k,g,h) in T, (p,q,r,s,t) in T:
      !(i=p and j=q and k=r and g=s and h=t)}
   dk[i,j,k,g,h,p,q,r,s,t] :=
   dk[i,j,k,g,h,p,q,r,s,t] + rhok*R[i,j,k,g,h,p,q,r,s,t];
 let {(i,j,k,g,h) in T} ck[i,j,k,g,h] := c[i,j,k,g,h];
 let {(i,j,k,g,h) in T} yk[i,j,k,g,h] := y[i,j,k,g,h];

 if etak == etamin then { printf "Stopping: etak = etamin\n"; break; }
 let etak := max(etak*etafac, etamin);
}

```

## pTax5Dnclipopt.run

```
else       $\rho_{k+1} \leftarrow 10\rho_k$ 

else    # keep previous solution; increase rhok
{ let {{i,j,k,g,h}} in T} c[i,j,k,g,h] := ck[i,j,k,g,h];
  let {{i,j,k,g,h}} in T} y[i,j,k,g,h] := yk[i,j,k,g,h];

  if  rhok == rhomax then { printf "Stopping: rhok = rhomax\n"; break; }
  let rhok := min(rhok*rhofac, rhomax);
}
} # end main loop
```

# Numerical results

# NCL/IPOPT on problem TAX

$na, nb, nc, nd, ne = 5, 3, 3, 2, 2 \quad m = 32220 \quad n = 360$

$k$	$\rho_k$	$\eta_k$	$\ r_k^*\ _\infty$	$\phi(x_k^*)$	<code>mu_init</code>	ltns	Time
1	$10^2$	$10^{-2}$	7.0e-03	-4.2038075e+02	$10^{-1}$	95	41.1
2	$10^2$	$10^{-3}$	4.1e-03	-4.2002898e+02	$10^{-4}$	17	7.2
3	$10^3$	$10^{-3}$	1.3e-03	-4.1986069e+02	$10^{-4}$	20	8.1
4	$10^4$	$10^{-3}$	4.4e-04	-4.1972958e+02	$10^{-4}$	48	25.0
5	$10^4$	$10^{-4}$	2.2e-04	-4.1968646e+02	$10^{-4}$	43	20.5
6	$10^5$	$10^{-4}$	9.8e-05	-4.1967560e+02	$10^{-4}$	64	32.9
7	$10^5$	$10^{-5}$	6.6e-05	-4.1967177e+02	$10^{-4}$	57	26.8
8	$10^6$	$10^{-5}$	4.2e-06	-4.1967150e+02	$10^{-4}$	87	46.2
9	$10^6$	$10^{-6}$	9.4e-07	-4.1967138e+02	$10^{-4}$	96	53.6

527 iterations, 5 mins CPU

# NCL/IPOPT on problem TAX

$na, nb, nc, nd, ne = 5, 3, 3, 2, 2 \quad m = 32220 \quad n = 360$

Constraints within tol of being active:  $c_i(x) \leq tol$

$tol$	$count$	$count/n$
$10^{-10}$	548	1.5
$10^{-9}$	550	1.5
$10^{-8}$	591	1.6
$10^{-7}$	890	2.5
→ $10^{-6}$	1104	3.1 ← About $3n$ active constraints
$10^{-5}$	1225	3.4
$10^{-4}$	1301	3.6
$10^{-3}$	1655	4.6
$10^{-2}$	3483	9.7
$10^{-1}$	10280	28.6

# NCL/IPOPT bigger example

$na, nb, nc, nd, ne = 21, 3, 3, 2, 2 \quad m = 570780 \quad n = 1512$

$k$	$\rho_k$	$\eta_k$	$\ r_k^*\ _\infty$	$\phi(x_k^*)$	mu_init	ltns	Time
1	$10^2$	$10^{-2}$	5.1e-03	-1.7656816e+03	$10^{-1}$	825	7763.3
2	$10^2$	$10^{-3}$	2.4e-03	-1.7648480e+03	$10^{-4}$	66	472.8
3	$10^3$	$10^{-3}$	1.3e-03	-1.7644006e+03	$10^{-4}$	106	771.3
4	$10^4$	$10^{-3}$	3.8e-04	-1.7639491e+03	$10^{-5}$	132	1347.0
5	$10^4$	$10^{-4}$	3.2e-04	-1.7637742e+03	$10^{-5}$	229	2450.9
6	$10^5$	$10^{-4}$	8.6e-05	-1.7636804e+03	$10^{-6}$	104	1096.9
7	$10^5$	$10^{-5}$	4.9e-05	-1.7636469e+03	$10^{-6}$	143	1633.4
8	$10^6$	$10^{-5}$	1.5e-05	-1.7636252e+03	$10^{-7}$	71	786.1
9	$10^7$	$10^{-5}$	2.8e-06	-1.7636196e+03	$10^{-7}$	67	725.7
10	$10^7$	$10^{-6}$	5.1e-07	-1.7636187e+03	$10^{-8}$	18	171.0

1761 iterations, 5 hours CPU

# NCL/IPOPT bigger example

$na, nb, nc, nd, ne = 21, 3, 3, 2, 2 \quad m = 570780 \quad n = 1512$

Constraints within tol of being active:  $c_i(x) \leq tol$

$tol$	$count$	$count/n$
$10^{-10}$	3888	2.6
$10^{-9}$	3941	2.6
$10^{-8}$	4430	2.9
$10^{-7}$	7158	4.7
→ $10^{-6}$	10074	6.6 ← $\approx 6.6n$ active constraints
$10^{-5}$	11451	7.6
$10^{-4}$	13109	8.7
$10^{-3}$	23099	15.3
$10^{-2}$	66361	43.9
$10^{-1}$	202664	134.0

# Comparison of IPOPT, KNITRO, NCL

$$na = \text{increasing} \quad nb = 3 \quad nc = 3 \quad nd = 2 \quad ne = 2$$

			IPOPT		KNITRO		NCL/IPOPT	
$na$	$m$	$n$	itns	time	itns	time	itns	time
5	32220	360	449	217	168	53	322	146
9	104652	648	> 98*	> 360*	928	825	655	1023
11	156420	792	> 87*	$\infty!$	2769	4117	727	1679
17	373933	1224			2598	11447	1021	6347
21	570780	1512					1761	17218

\*duals diverge

MUMPS needs more mem

!Loop

**A future possibility  
AMPL + IPM + 2nd derivatives**

## KNOSSOS via AMPL + IPM?

Stabilized LCL (Friedlander and S, 2005) is equivalent to a BCL method:

$$\begin{aligned} \text{ELC}_k & \underset{x}{\text{minimize}} && L(x, y_k, \rho_k) + \sigma_k \|\bar{c}_k(x)\|_1 \\ & \text{subject to} && \ell \leq x \leq u \end{aligned}$$

- $\bar{c}_k(x)$  = linear approximation to  $c(x)$  at  $x_k$  (MINOS has very big  $\sigma_k$ )

# KNOSSOS via AMPL + IPM?

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- $\bar{c}_k(x)$  = linear approximation to  $c(x)$  at  $x_k$  (MINOS has very big  $\sigma_k$ )

$$\begin{aligned} \text{ELC}''_k & \underset{x, v, w}{\text{minimize}} \quad M_k(x, v, w) + \sigma_k e^T(v + w) \\ & \text{subject to } \bar{c}_k(x) + v - w = 0, \quad \ell \leq x \leq u, \quad v, w \geq 0 \end{aligned}$$

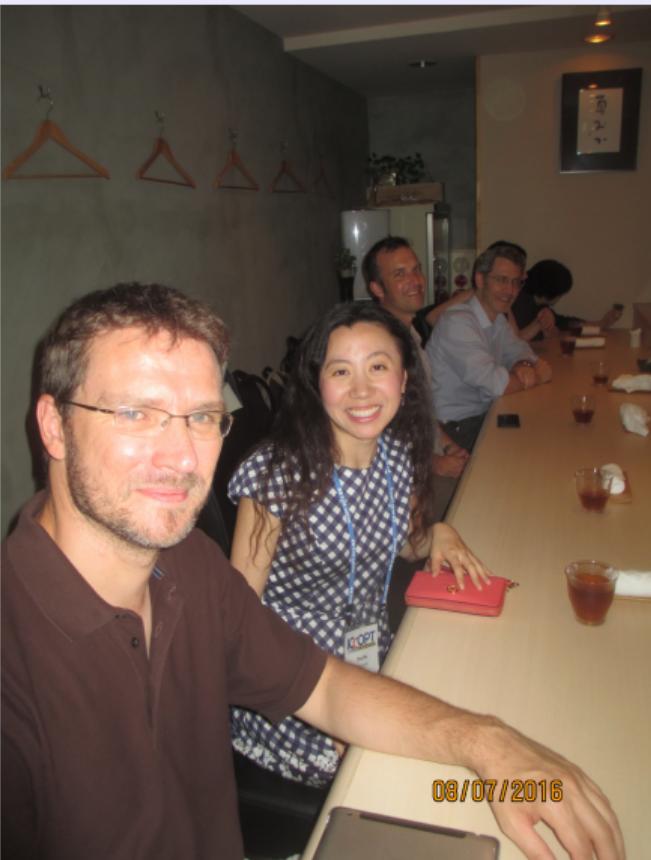
- $M_k$  = modified augmented Lagrangian  $d_k(x, v, w) = c(x) - \bar{c}_k(x) - v + w$
- IPOPT, KNITRO, ... won't mind the extra elastic variables  $v, w$

## Special thanks

- LANCELOT: Andy, Nick, Philippe
- AMPL: Bob Fourer, Dave Gay
- IPOPT: Larry Biegler, Andreas Wächter
- Katya and all the Workshop Committee
- Yuja Wang, youtube
- Coauthors: Ken Judd, Dominique Orban  
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# Oman Jan 2017



# Mehi Al-Baali + Lancelot



# Dave and Bob — AMPL!



01/04/2016

# Larry and Andreas — IPOPT!

Thursday February 2, 2017

## Graduate Seminar

Chemical Engineering Welcomes

# Lorenz T. Biegler



### Three Paradigms for the Future of Process Optimization

**Abstract:** Computer aided process engineering (CAPE) requires the determination of superior systems with reduced costs, increased efficiency or improved operability. These solutions especially need to consider complex unit operations with engineering and physics-based models. On the other hand, while process engineers need to synthesize and optimize processes with sufficiently detailed models, most engineering software tools still struggle with optimization of an integrated process. This overview explores three strategic paradigms that enable the realization of effective optimization strategies for large-scale process models, including complex models at device and molecular scales.



