# Introduction to Column Generation

CPAIOR Master Class – 2016 - Banff







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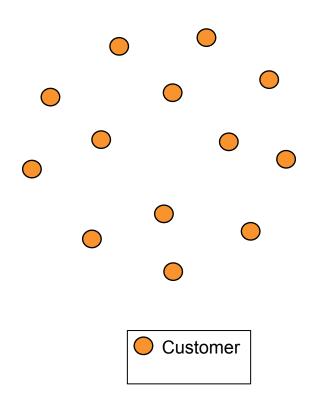
CIRRELT - POLYTECHNIQUE MTL



An example
Vehicle routing problem

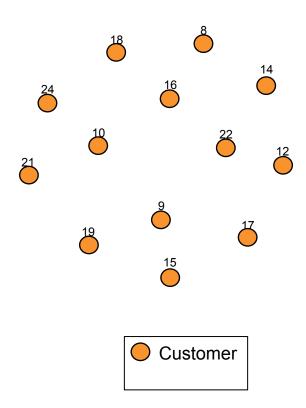


Customers



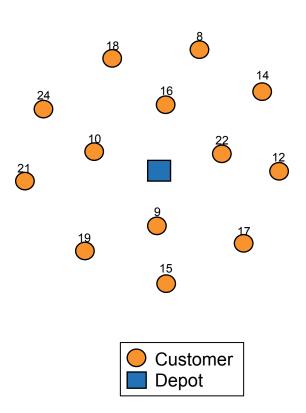


- Customers
  - Demand constraints



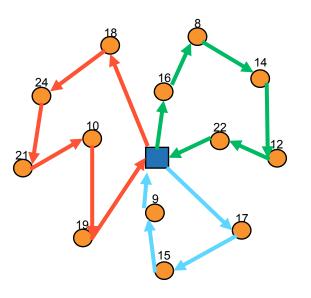


- Customers
  - Demand constraints
- Vehicles
  - -Capacity constraints
  - Flow conservation constraints





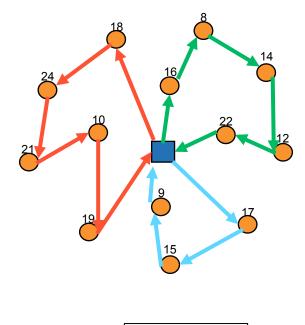
- Customers
  - Demand constraints
- Vehicles
  - Capacity constraints
  - Flow conservation constraints
- Objective:
  - Find routes that minimize total distance







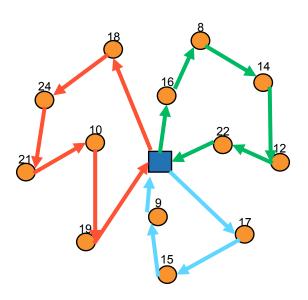
- Standard mip formulation:
  - Scaling issues
  - Symmetry
  - More complex constraints add even more complexity
  - Some constraints can lead to bad linear relaxations.







- Standard mip formulation:
  - Scaling issues
  - Symmetry
  - More complex constraints add even more complexity
  - Some constraints can lead to bad linear relaxations.
- Enumerate all possible routes
  - Much simpler formulation
  - Vehicle constraints are implicitly considered in route enumeration
  - Better Linear Relaxation





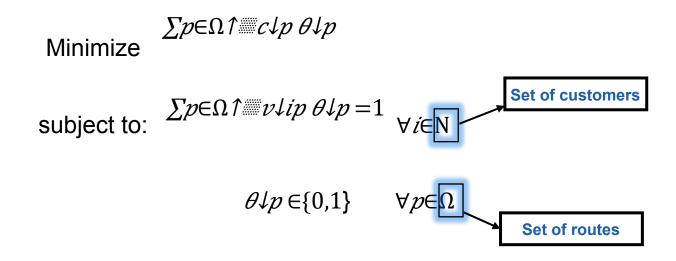


$$\sum p \in \Omega \uparrow \text{ } \text{ } \text{ } \text{ } c \downarrow p \text{ } \theta \downarrow p$$
 Minimize

subject to: 
$$\sum p \in \Omega \uparrow \text{with } \theta \downarrow p = 1 \quad \forall i \in \mathbb{N}$$

$$\theta \downarrow p \in \{0,1\} \quad \forall p \in \Omega$$

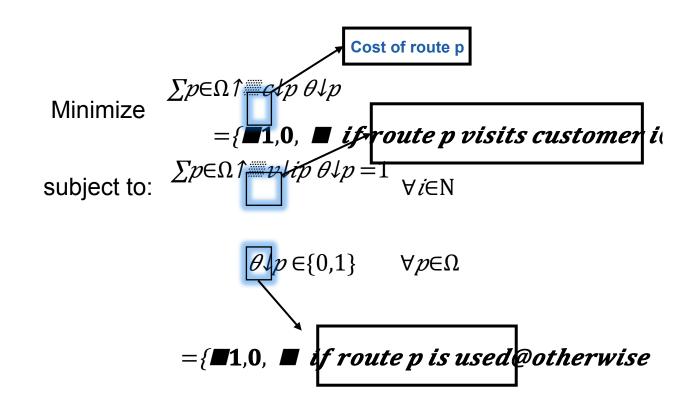




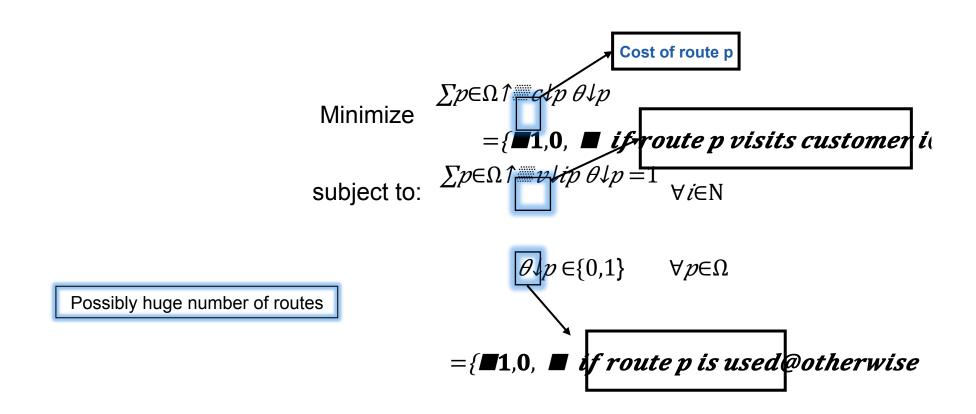


Minimize 
$$\sum p \in \Omega \uparrow \text{ if } route \ p \text{ is used } \text{ otherwise}$$
 Subject to: 
$$\sum p \in \Omega \uparrow \text{ if } route \ p \text{ is used } \text{ otherwise}$$

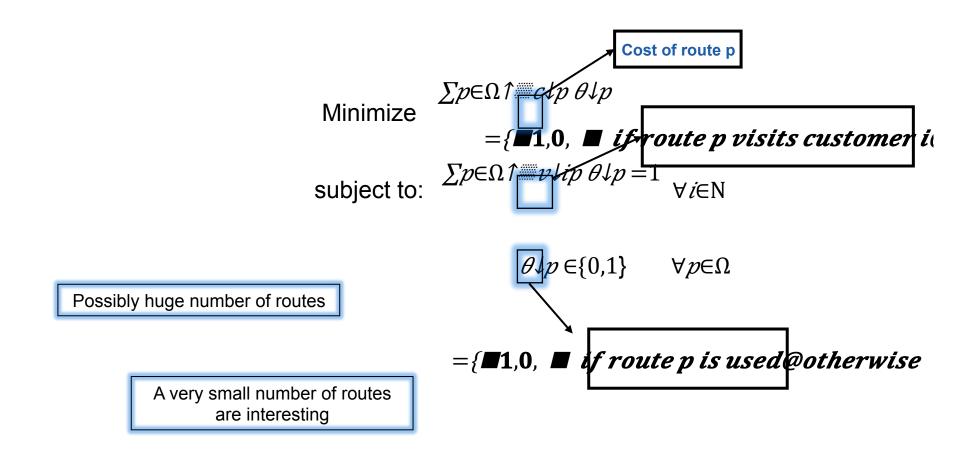


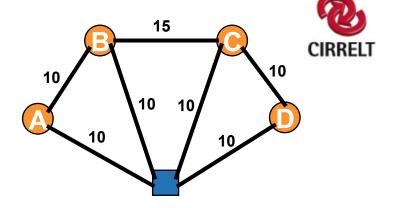














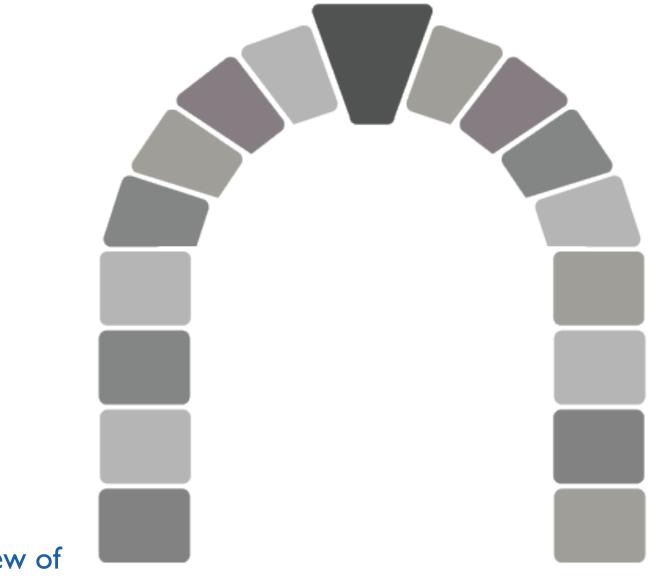
Min 
$$20 x l 1 + 20 x l 2 + 20 x l 3 + 20 x l 4 + 30 x l 5 + 30 x l 6 + 35 x l 7$$

A:  $x l 1 + x l 5 = 1$ 

B:  $+x l 2 + x l 3 + x l 6 + x l 7 = 1$ 

C:  $+x l 3 + x l 6 + x l 7 = 1$ 

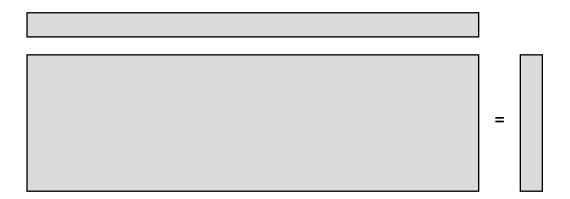
D:  $+x l 4 + x l 6 + x l 7 = 1$ 



An intuitive view of

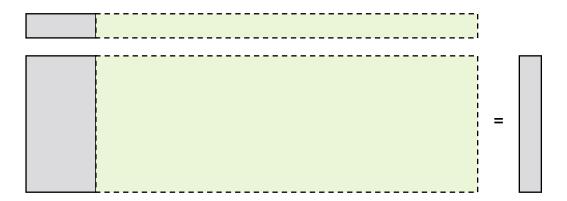


Solve linear programs with a lot of variables



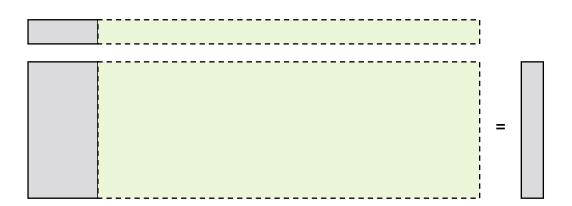


- Solve linear programs with a lot of variables
  - Solve with a subset of variables





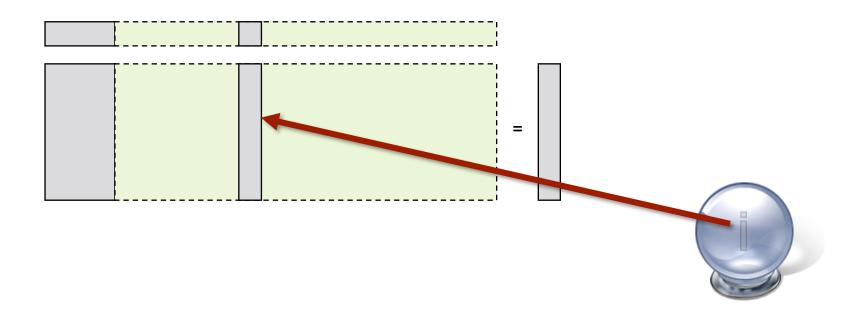
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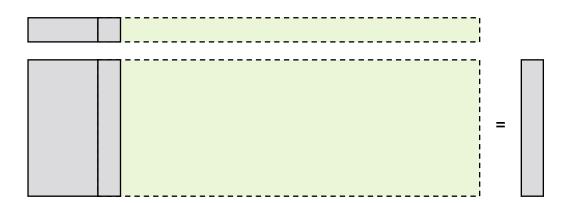


- Solve linear programs with a lot of variables
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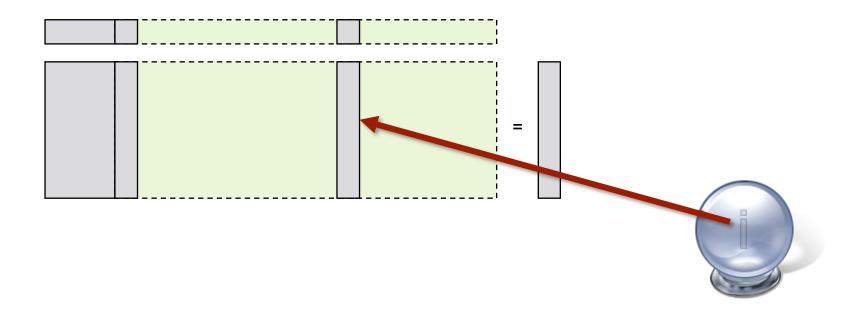
- Solve linear programs with a lot of variables
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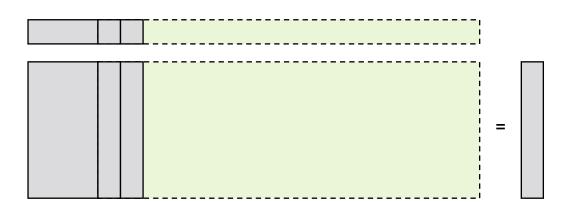


- Solve linear programs with a lot of variables
  - Solve with a subset of variables





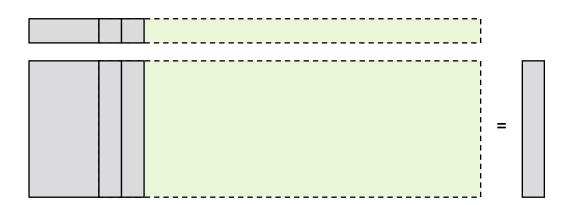
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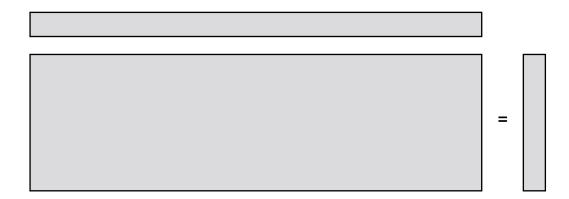
- Solve linear programs with a lot of variables
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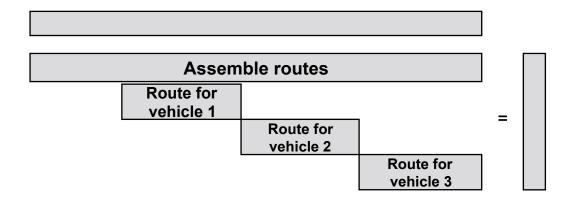


• When to use column generation?



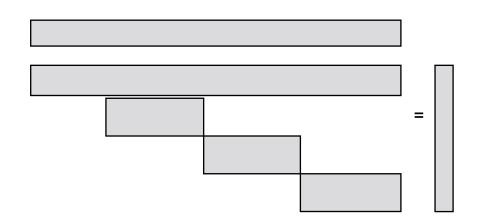


• When to use column generation?





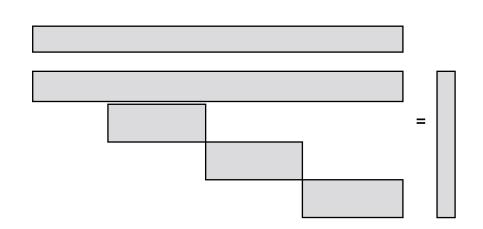
- When to use column generation?
- Works well generally on:
  - Vehicle routing
  - Airline Scheduling
  - Shift Scheduling
  - Jobshop Scheduling
  - <del>-</del> ...
- Multi-level of assembly





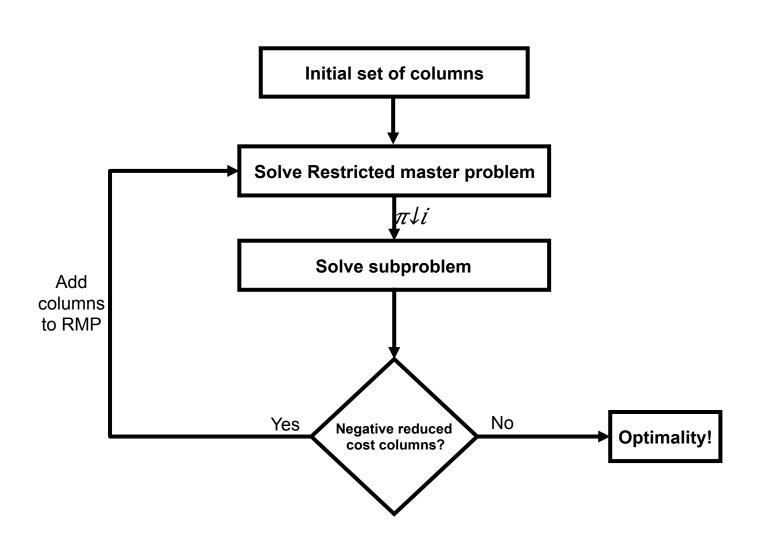
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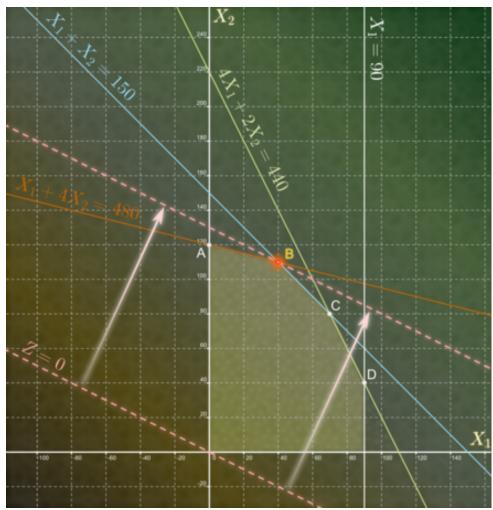
<del>-</del> . . .



- Multi-level of assembly
- Worked the best when part of the problem has an underlying structure: Network, Hypergraph, knapsack, etc...

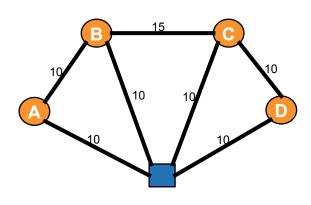






Master Probelm for the Vehicle routing problem

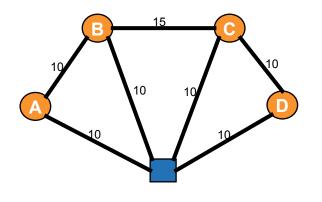








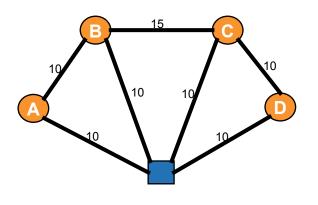
Min	20 <i>x↓</i> 1	+20 <i>x</i> √2	+20 <i>x</i> \$\dagger\$	+20 <i>x</i> ↓4	
<b>A</b> :	<i>x\</i> 1				= 1
B :		<i>x</i> .12			= 1
<b>C</b> :			x13		= 1
D:				<i>x</i> ↓4	= 1







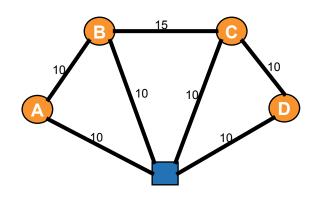
	<i>x</i> . <i>l</i> 1	<i>x</i> .12	<i>x</i> .\$3	<i>x</i> ↓4	
Min	20	20	20	20	
<b>A</b> :	1				= 1
B :		1			= 1
<b>C</b> :			1		= 1
D:				1	= 1







	x l 1	<i>x</i> ↓2	<i>x</i> ↓3	<i>x1</i> 4		
Ĉ	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				= 1	20
B :		1			= 1	20
<b>C</b> :			1		= 1	20
D:				1	= 1	20
	1	1	1	1	80	

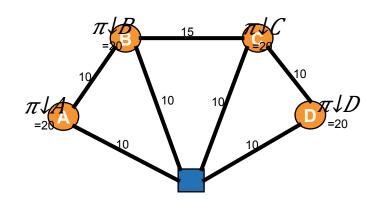






An example (max 2 clients)

	<i>x</i> ↓1	<i>x</i> \$2	<i>x</i> ↓3	<i>x</i> ↓4		
ĉ	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				= 1	20
B :		1			= 1	20
<b>C</b> :			1		= 1	20
D:				1	= 1	20
	1	1	1	1	80	



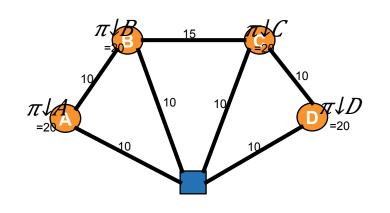


 $\pi \downarrow i$ : Marginal price of visiting customer I



An example (max 2 clients)

	xl1	<i>x</i> \$2	<i>x</i> .\$43	<i>x1</i> 4		
ĉ	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				= 1	20
B :		1			= 1	20
<b>C</b> :			1		= 1	20
D:				1	= 1	20
	1	1	1	1	80	



 $\pi \downarrow i$ : Marginal price of visiting customer I

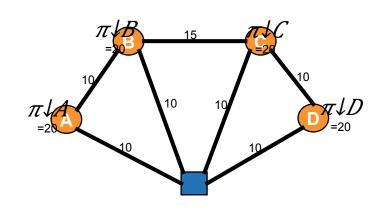
Can I find a route such that:  $c < \sum 1 = \pi \sqrt{i}$ 





An example (max 2 clients)

	<i>x\</i> 1	<i>x</i> \$2	<i>x</i> .\$\dag{3}	<i>x1</i> 4		
ĉ	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				= 1	20
B :		1			= 1	20
<b>C</b> :			1		= 1	20
<u>D:</u>				1	= 1	20
	1	1	1	1	80	



 $\pi \downarrow i$ : Marginal price of visiting customer I

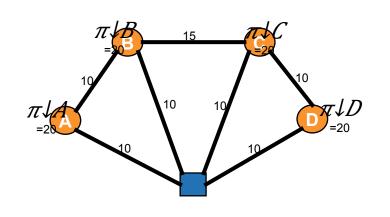
Can I find a route such that:  $c-\sum 1 m\pi i < 0$ 



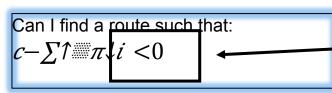


An example (max 2 clients)

	<i>x</i> \$1	<i>x</i> .12	<i>x</i> . <i>l</i> 3	<i>x</i> \$4		
Ĉ	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				= 1	20
B :		1			= 1	20
<b>C</b> :			1		= 1	20
D:				1	= 1	20
	1	1	1	1	80	



 $\pi \downarrow i$ : Marginal price of visiting customer I



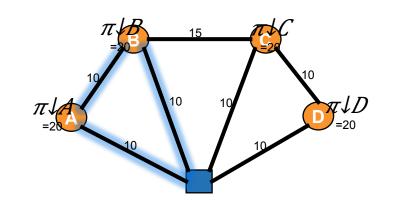
Reduced cost!

Customer Depot



An example (max 2 clients)

	<i>x1</i> 1	<i>x</i> ↓2	<i>x</i> ↓3	<i>x</i> .14		
ĉ	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				= 1	20
B :		1			= 1	20
<b>C</b> :			1		= 1	20
<u>D:</u>				1	= 1	20
	1	1	1	1	80	





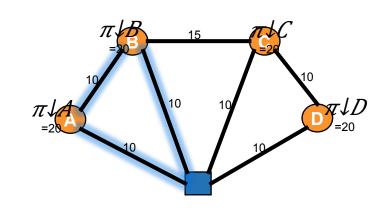
 $\pi \downarrow i$ : Marginal price of visiting customer I

Can I find a route such that:  $c-\sum 1 = \pi i$ 



An example (max 2 clients)

	<i>x\</i> 1	<i>x</i> \$2	<i>x</i> .\$\dag{3}	<i>x</i> ↓4	<i>x↓</i> 5		
Ĉ	0	0	0	0	-10		$\pi \downarrow i$
<b>A</b> :	1				1	= 1	20
B :		1			1	= 1	20
<b>C</b> :			1			= 1	20
D:				1		= 1	20
	1	1	1	1		80	





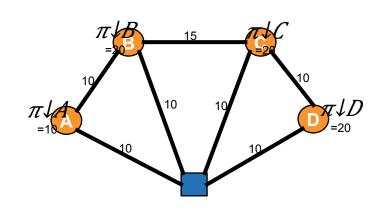
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Can I find a route such that:  $c-\sum 1 = \pi i$ 



An example (max 2 clients)

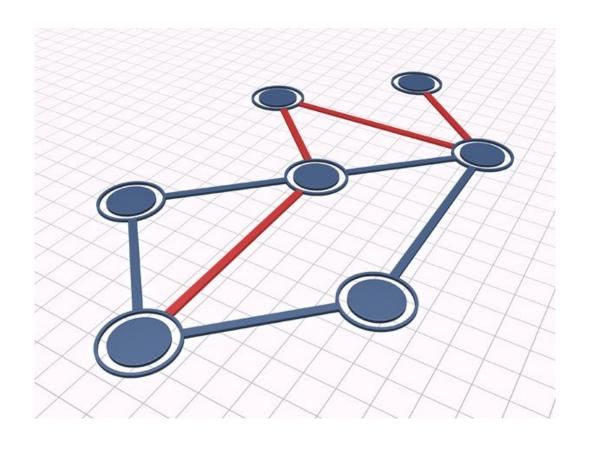
	<i>x\</i> 1	<i>x</i> ↓2	<i>x</i> ↓3	<i>x1</i> 4	<i>x</i> \$15		
Ĉ	10	0	0	0	0		$\pi \downarrow i$
<b>A</b> :	1				1	= 1	10
B :		1			1	= 1	20
<b>C</b> :			1			= 1	20
D:				1	-	= 1	20
		0	1	1	1	70	





 $\pi \downarrow i$ : Marginal price of visiting customer I

Can I find a route such that:  $c-\sum 1 = \pi i$ 



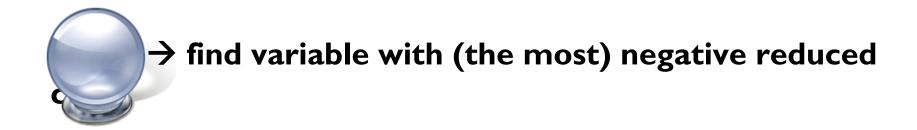
Sub Probelm for the Vehicle routing problem

## General Subproblem



- Implicit representation of all variables
  - Every possible solution to the subproblem is a variable

Optimization objective:



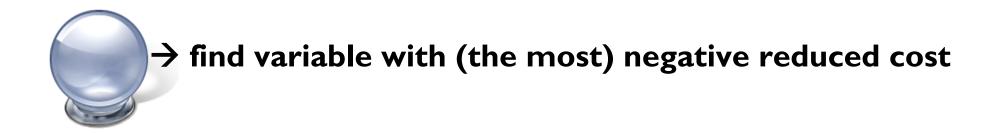
Min  $\hat{c}=c-\sum i \uparrow \text{ as it } \{\blacksquare 1,0, \blacksquare \text{ if customer i is visited@otherwill}\}$ 

#### General Subproblem



- Implicit representation of all variables
  - Every possible solution to the subproblem is a variable

Optimization objective:



Min  $\hat{c}=c-\sum i\uparrow \text{ as interval}$  **Interval**  $c=\sum x\uparrow \text{ as } c\downarrow x$  x

#### Subproblem



- Implicit representation of all variables
  - Every possible solution to the subproblem is a variable
- Optimization objective:



find variable with (the most) negative reduced cost

Min  $\hat{c} = \sum x \uparrow = c \downarrow x x - \sum i \not = i \uparrow = i \downarrow = i \downarrow$ 

#### Subproblem



- Implicit representation of all variables
  - Every possible solution to the subproblem is a variable
- Optimization objective:



> find variable with (the most) negative reduced cost

Min  $\hat{c} = \sum x \uparrow = c \downarrow x x - \sum i \uparrow = \pi \downarrow i \ a \downarrow i$  if customer i is visited@ot

Subject to: Capacity constraints

Flow conservation constraints

Shortest-path problem with resource constraints:

Dynamic programming

#### Resources Constraint SPP



- Resource r = 1,...,R
- Resource consumption  $t_{ij}^r > 0$  on each arc.
- Resources window[a<sup>r</sup><sub>i</sub>,b<sup>r</sup><sub>i</sub>] at each node
  - Resources level cannot go above b<sup>r</sup>, when node v<sub>i</sub> is reached
  - If  $t_{ij}^r$  is below  $a_i^r$  when node path reaches  $v_i$  then is it set to  $a_i^r$

#### Resources Constraint SPP - DP



- Dynamic Programming Algorithm
  - -L<sub>i</sub>: list of labels associated with node v<sub>i</sub>
  - -label  $I = (c,T^1,...,T^R)$  where
    - c is the cost of the label
    - T<sup>r</sup> is the consumption level of resource r
    - a label represents a partial path from v<sub>0</sub> to v<sub>i</sub>
    - v(l) is the node which to which I is associated

#### Resources Constraint SPP - DP



- Extending a label  $I = (c, T_i^1, ..., T_i^R)$  from  $v_i$  to  $v_j$ 
  - Create a label (c +  $c_{ij}$ ,  $T^I + t^I_{ij}$ ,...,  $T^R + t^R_{ij}$ )
    - Making sure we respect  $[a_i^l, b_i^l], ..., [a_i^R, b_i^R]$
  - Insert the label in the list of labels associated with  $v_i$
  - Apply **Dominance Rules** 
    - Without such rules, the algorithm would enumerates all possible paths
  - Resources constraints make sure the algorithm terminates

#### Resources Constraint SPP - DP



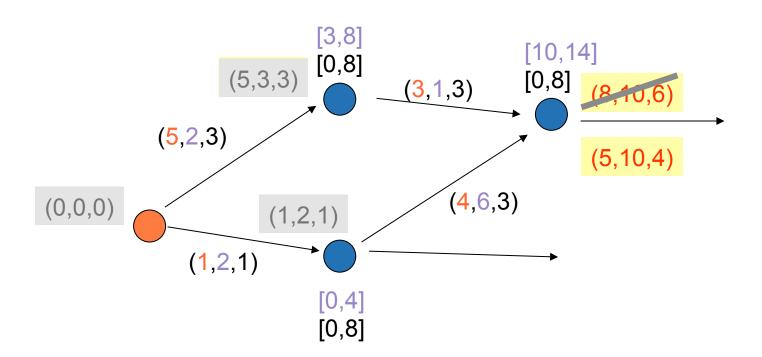
• Dominance Rules: I<sub>1</sub> dominates I<sub>2</sub> iff:

$$-c(l_1) \le c(l_2)$$

- Every feasible **future** extension of l<sub>2</sub> will be feasible for l<sub>1</sub>
  - Most often we check that  $T^r(I_1) \le T^r(I_2)$  for all r

## Dominance: an example





#### Subproblem – Constraint Programming



"Arc Flow" model

Objectives:

- Minimize:  $\sum_{i}$  (ReducedCost(i,  $S_{i}$ ))

Variables:

 $-S_i \in N$ 

 $-V_i \in \{False, True\}$ 

 $-I_i \in [0..Capacity]$ 

Successor of node i

Node i visited by current path

Truck load after visit of node i

Constraints:

 $-S_i = i \rightarrow V_i = False$ 

AllDiff(S)

– NoSubTour(S)

 $-S_i = j \rightarrow I_i + D_j = I_j$ 

S-V Coherence constraints

Conservation of flow

SubTour elimination constraint

Capacity constraints

+ Redundant Constraints from work on TSP(TW)

#### Subproblem – Constraint Programming



"Position" model

Objectives:

- Minimize:  $\sum_{k}$  (ReducedCost( $P_k$ ,  $P_{k+1}$ ))

Variables:

 $-P_k \in N$ 

 $-L_k \in [0..Capacity]$ 

Node visited a position k

Truck load after visiting position k

Constraints:

– AllDiff(P)

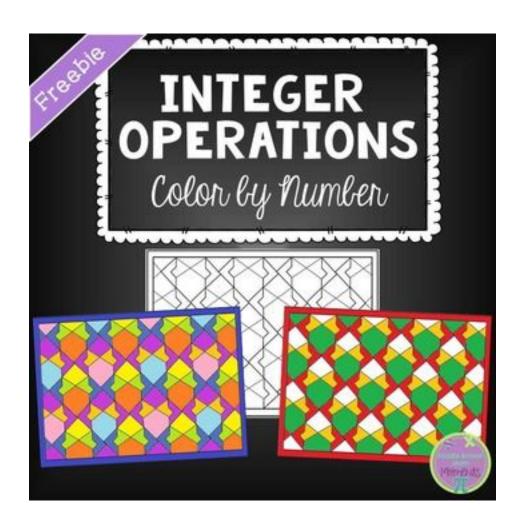
 $- L_{k+1} = L_k + D_{Pk}$ 

 $-P_k = depot \rightarrow P_{k+1} = depot$ 

Elementarity of the path

Capacity constraints

Padding at the end of path



Obtaining integer solutions



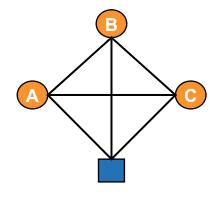
- Column generation + MIP: Branch-and-price
  - How to obtain integer solutions?



- Column generation + MIP: Branch-and-price
  - How to obtain integer solutions?
    - Branch-and-bound -> solve LP relaxation at each node
    - Branch-and-price -> column generation to solve LP relaxation at each node

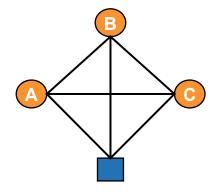


- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I





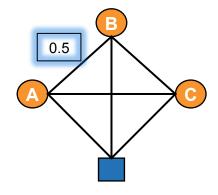
- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I



	$x \downarrow$	$x \downarrow$	xl	
	1	2	3	
Min	3	3	3	
A:	1	1		= 1
В:	1		1	= 1
<b>C</b> :		1	1	= 1
OptSol:	0.5	0.5	0.5	4.5



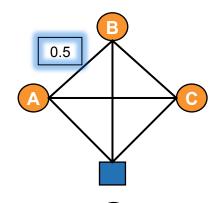
- Vehicle routing problem
  - Max 2 customers
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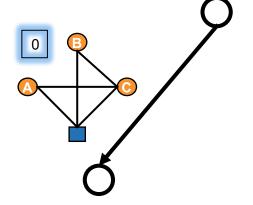


	x l	$x \downarrow$	xl	
	1	2	3	
Min	3	3	3	
A:	1	1		= 1
B:	1		1	= 1
<b>C</b> :		1	1	= 1
OptSol:	0.5	0.5	0.5	4.5



- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I





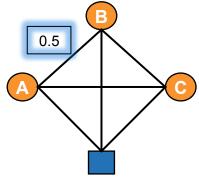
		$x \downarrow$	$x \downarrow$	xl	
_		1	2	3	
	Min	3	3	3	
•	A :	1	1		= 1
	B :	1		1	= 1
	C :		1	1	= 1
	OptSol:	0.5	0.5	0.5	4.5

**OptSol**: 0.5 0.5 0.5 4.5

	x l	$x \downarrow$	xl	
	1	2	3	
Min	3	3	3	
A :	1	1		= 1
B:			1	= 1
<b>C</b> :		1	1	= 1

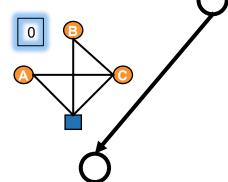


- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I



0.5		xl	xl	xl	
		1	2	3	
	Min	3	3	3	
	A :	1	1		= 1
	B :	1		1	= 1
	<b>C</b> :		1	1	= 1
O	OptSol:	0.5	0.5	0.5	4.5

	$x \downarrow$	
	4	
	2	
<b>A</b> :	1	11
B :		4
C·		



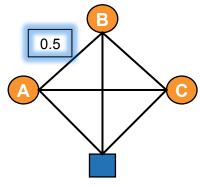
	$x \downarrow$	$x \downarrow$	$x \downarrow$	
	1	2	3	
Min	3	3	3	
A:	1	1		= 1
_				

**C** :

	$x \downarrow$	$x \downarrow$	xl	
	1	2	3	
Min	3	3	3	
A:	1	1		= 1
B :			1	= 1



- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I



$x \downarrow$	
4 2	0
A: 1	
B: <b>*</b>	

0	
0	·
$\cup$	

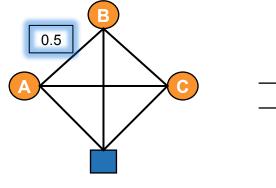
		$x \downarrow$	$x \downarrow$	$x \downarrow$	
_		1	2	3	
	Min	3	3	3	
	A :	1	1		= 1
	В:	1		1	= 1
	<b>C</b> :		1	1	= 1
	OptSol:	0.5	0.5	0.5	4.5

	$x \downarrow$	$x \downarrow$	$x \downarrow$	xl	
	1	2	3	4	
Min	3	3	3	2	
A :	1	1		1	= 1
B :			1		= 1
<b>C</b> ·		1	1		_ 1

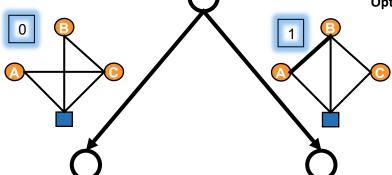
**C** :



- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I



	хĮ	хĮ	x l	
	1	2	3	
Min	3	3	3	
A:	1	1		= 1
B :	1		1	= 1
<b>C</b> :		1	1	= 1
OptSol:	0.5	0.5	0.5	4.5

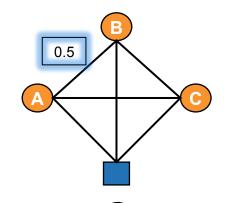


		$x \downarrow$	$x \downarrow$	x l	$x \downarrow$	
		1	2	3	4	
M	in	3	3	3	2	
P	١:	1	1		1	= 1
E	3 :			1		= 1
	<u>.</u>		1	1		= 1

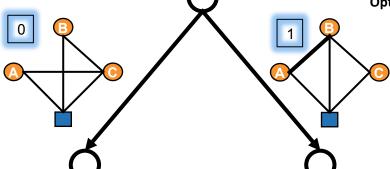
	<i>x</i> ↓ 1	$x \downarrow$ 2	<i>x↓</i> 3	
Min	3	3	3	
A:	1	1		= 1
B :	1		1	= 1
<b>C</b> :			1	= 1



- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I



	$x \downarrow$	$x \downarrow$	xl	
	1	2	3	
Min	3	3	3	
A :	1	1		= 1
B:	1		1	= 1
C:		1	1	= 1
OntSol	0.5	0.5	٥ ـ ٦	15



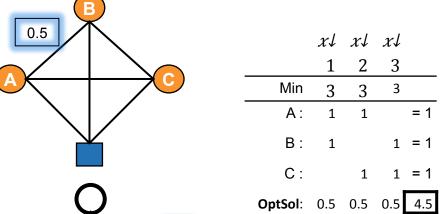
	xI	$x \downarrow$	xI	$x \downarrow$	
	1	2	3	4	
Min	3	3	3	2	
A :	1	1		1	= 1
B :			1		= 1
<b>.</b>		4	4		_ 1

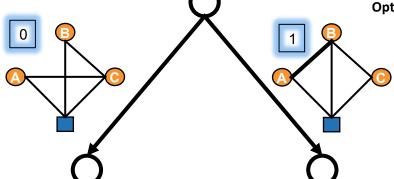
	$x \downarrow$	$x \downarrow$	$x \downarrow$	xl	
	1	2	3	5	
Min	3	3	3	2	
A :	1	1			= 1
B :	1		1		= 1
<b>C</b> :			1	1	= 1



- Vehicle routing problem
  - Max 2 customers
  - Cost of all arc: I

# Why branch on arc-flow variables?



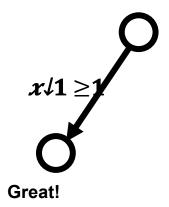


	$x \downarrow$	$x \downarrow$	$x \downarrow$	x l	
	1	2	3	4	
Min	3	3	3	2	
<b>A</b> :	1	1		1	= 1
В:			1		= 1
C·		1	1		= 1

	$x \downarrow$	$x \downarrow$	$x \downarrow$	xl	
	1	2	3	5	
Min	3	3	3	2	
A :	1	1			= 1
B:	1		1		= 1
<b>C</b> :			1	1	= 1

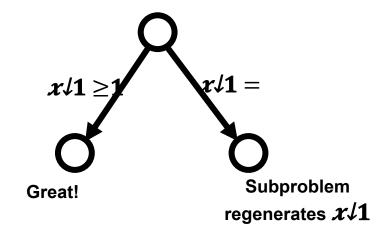


- Branching possibilities
  - Branch on master variables





- Branching possibilities
  - Branch on master variables





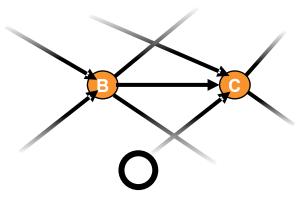
- Branching possibilities
  - Branch on master variables... NO!



- Branching possibilities
  - Branch on master variables... NO!
  - Branch on subproblem variables

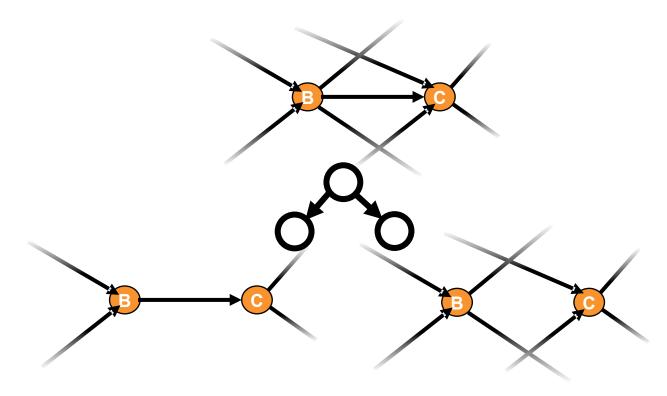


- Branching possibilities
  - Branch on master variables... NO!
  - Branch on subproblem variables



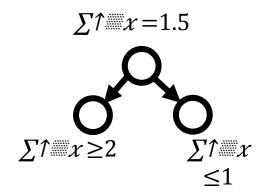


- Branching possibilities
  - Branch on master variables... NO!
  - Branch on subproblem variables





- Branching possibilities
  - Branch on master variables... NO!
  - Branch on subproblem variables
  - Branch on the master problem constraints
    - Add constraints c->  $\pi c \downarrow$  must be added to the subproblems
    - Example: Branch on the total number of vehicle used

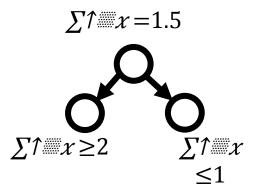


### Branch-and-price



- Branching possibilities
  - Branch on master variables... NO!
  - Branch on subproblem variables
  - Branch on the master problem constraint
    - Add constraints ->  $\pi \downarrow i$  to add to the subproblems
    - Example: Branch on the total number of vehicle used

Best branching for shift scheduling problem



### Branch-and-price



- Branching possibilities
  - Branch on master variables... NO!
  - Branch on subproblem variables
  - Branch on the master problem constraints
  - Cuts
    - Again dual variable  $\pi \downarrow$  must be added to add to the subproblems

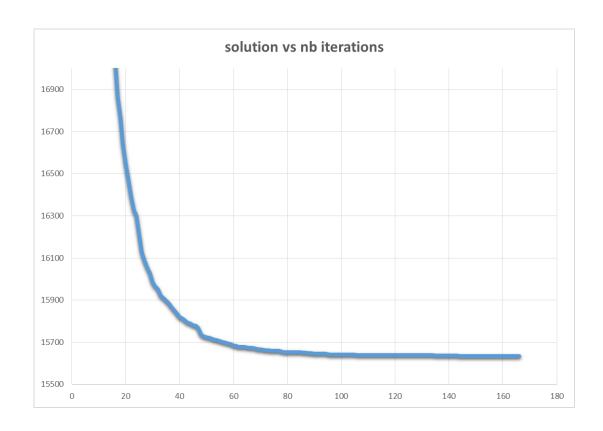


Applied column generation

Main Challenges

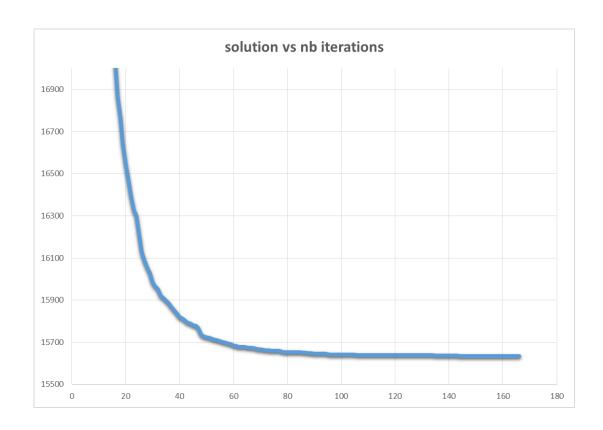


- Evolution of costs
  - Long convergence time



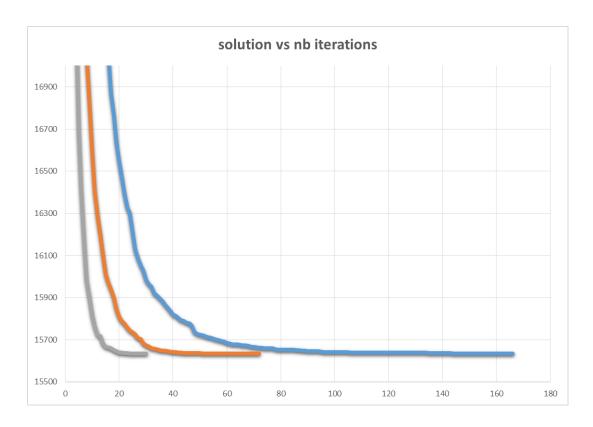


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns



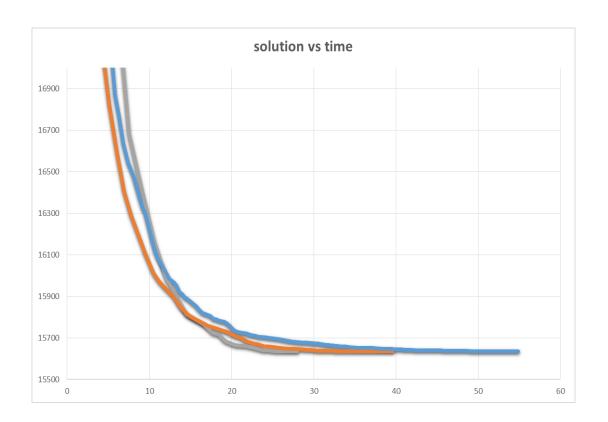


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns



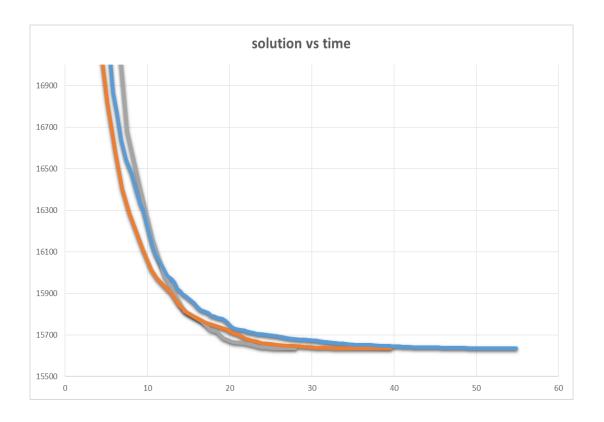


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns



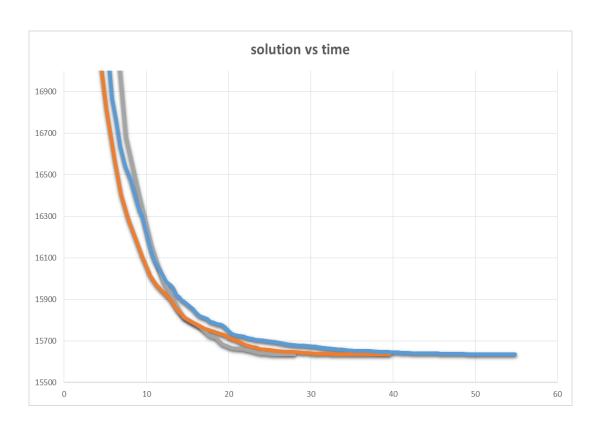


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns
  - Delete variables in RMP



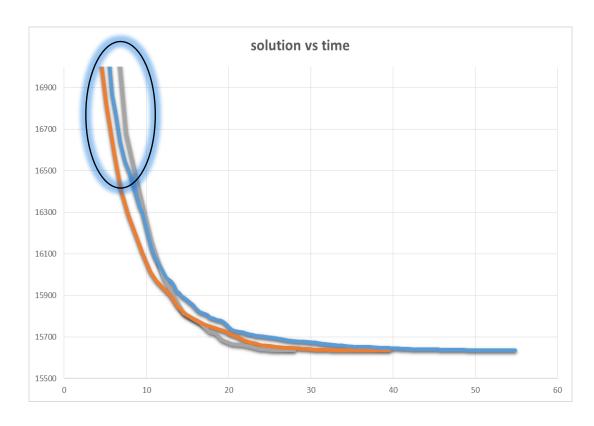


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns
  - Delete variables in RMP



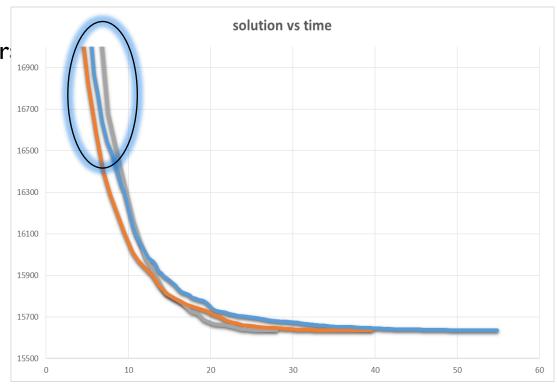


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns
  - Delete variables in RMP



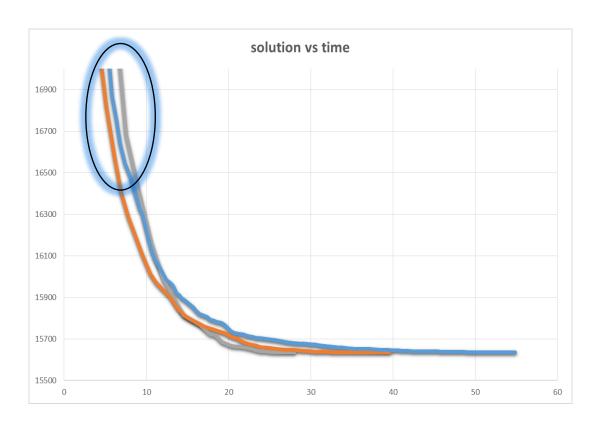


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to gener new columns
  - Delete variables in RMP
  - Gradually increase computation effort



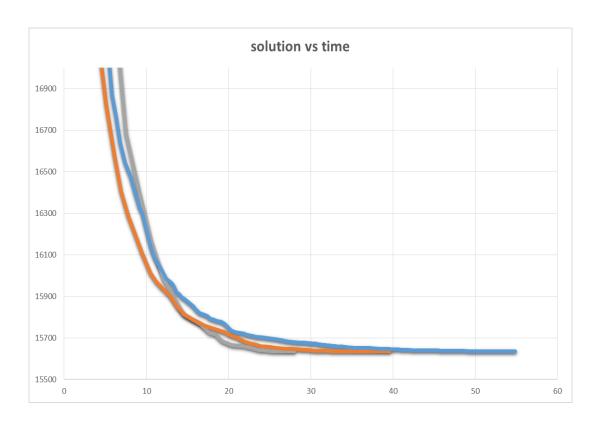


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns
  - Delete variables in RMP
  - Gradually increase computation effort
  - Heuristic pricing



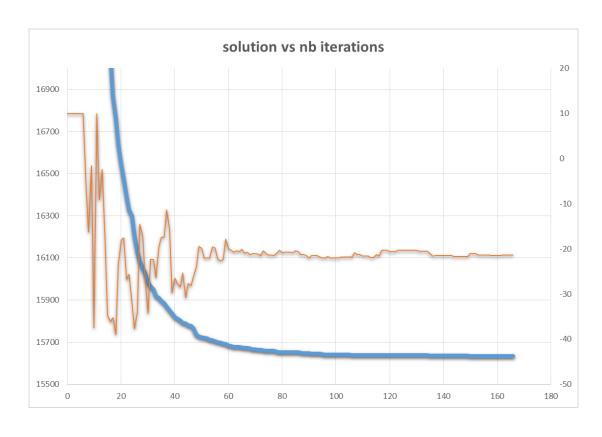


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns
  - Delete variables in RMP
  - Gradually increase computation effort
  - Heuristic pricing
  - Stabilization



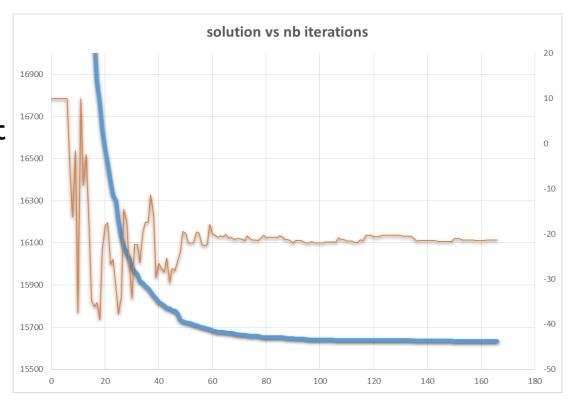


- Evolution of costs
  - Long convergence time
- Speed-up techniques
  - Spend more time to generate new columns
  - Delete variables in RMP
  - Gradually increase computation effort
  - Heuristic pricing
  - Stabilization





- Stabilization
  - Duals are extreme points
  - Master problem is degenerated
  - Tail-off effect is due to difficulty finding the right dual vector



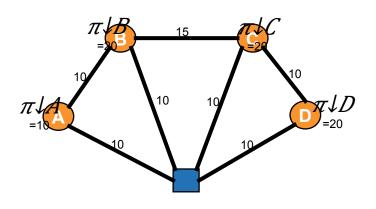


A quick look at

Stabilization issues



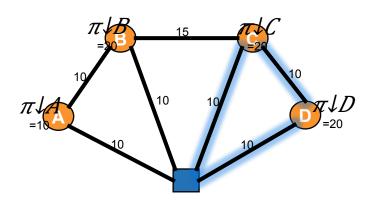
	$x \downarrow$	$x \downarrow$	$x \downarrow$	$x \downarrow$	xl		
	1	2	3	4	5		
Ĉ	10	0	0	0	0		$\pi \downarrow i$
A:	1				1	= 1	10
B :		1			1	= 1	20
<b>C</b> :			1			= 1	20
D:				1	_	= 1	20
		0	1	1	1	70	







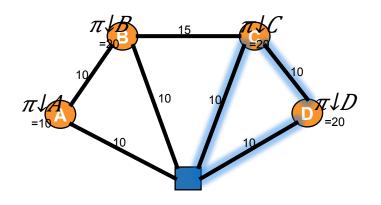
	x l	x l	$x \downarrow$	$x \downarrow$	$x \downarrow$		
	1	2	3	4	5		
Ĉ	10	0	0	0	0		$\pi \downarrow i$
A:	1				1	= 1	10
B :		1			1	= 1	20
<b>C</b> :			1			= 1	20
D:				1	_	= 1	20
		0	1	1	1	70	







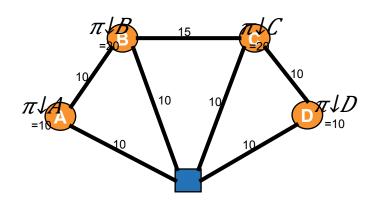
	$x \downarrow$	$x \downarrow$	$x \downarrow$	$x \downarrow$	x l	x l		
	1	2	3	4	5	6		
Ĉ	10	0	0	0	0	-10		$\pi \downarrow i$
A:	1				1		= 1	10
B :		1			1		= 1	20
<b>C</b> :			1			1	= 1	20
D:				1		1	= 1	20
		0	1	1	1		70	







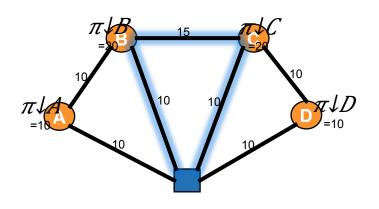
	$x \downarrow$							
	1	2	3	4	5	6		
Ĉ	10	0	0	10	0	0		$\pi \downarrow i$
<b>A</b> :	1				1		= 1	10
В:		1			1		= 1	20
<b>C</b> :			1			1	= 1	20
D:				1		1	= 1	10
		0	0		1	1	60	







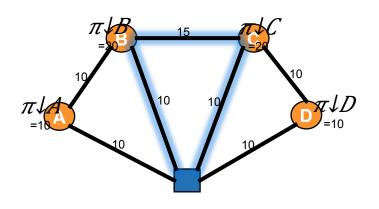
	$x \downarrow$	x l						
	1	2	3	4	5	6		
Ĉ	10	0	0	10	0	0		$\pi \downarrow i$
A:	1				1		= 1	10
B :		1			1		= 1	20
<b>C</b> :			1			1	= 1	20
D:				1		1	= 1	10
		0	0		1	1	60	







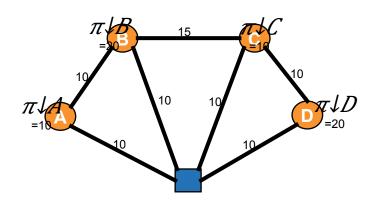
	$x \downarrow$	x l							
	1	2	3	4	5	6	7		
Ĉ	10	0	0	10	0	0	-5		$\pi \downarrow i$
A:	1				1			= 1	10
B :		1			1		1	= 1	20
<b>C</b> :			1			1	1	= 1	20
D:				1		1		= 1	10
		0	0		1	1		60	







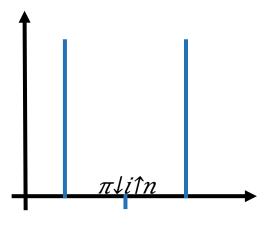
	$x \downarrow$	x l							
	1	2	3	4	5	6	7		
Ĉ	10	0	10	0	0	0	5		$\pi \downarrow i$
A:	1				1			= 1	10
B :		1			1		1	= 1	20
<b>C</b> :			1			1	1	= 1	10
D:				1		1		= 1	20
		0		0	1	1		60	





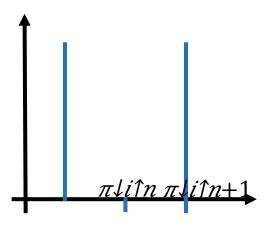


- Stabilization!
  - -What to do?
  - Popular technique
    - Box penalization



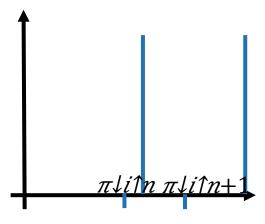


- Stabilization!
  - -What to do?
  - Popular technique
    - Box penalization



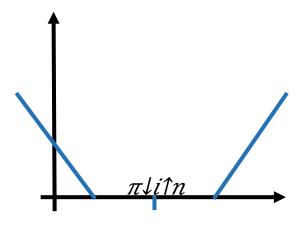


- Stabilization!
  - -What to do?
  - Popular technique
    - Box penalization





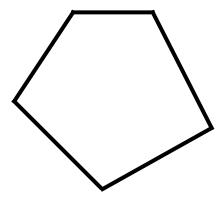
- Stabilization!
  - -What to do?
  - Popular technique
    - Box penalization





- Stabilization!
  - -What to do?
  - Popular technique
    - Box penalization
  - Interior point stabilization

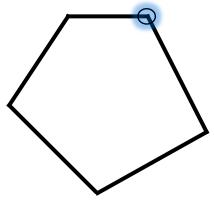






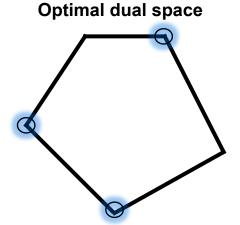
- Stabilization!
  - What to do?
  - Popular technique
    - Box penalization
  - Interior point stabilization
    - Adding a variable to the primal is equivalent to adding a cut to the dual





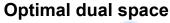


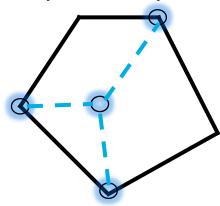
- Stabilization!
  - What to do?
  - Popular technique
    - Box penalization
  - Interior point stabilization
    - Find multiple dual optimal extreme points





- Stabilization!
  - What to do?
  - Popular technique
    - Box penalization
  - Interior point stabilization
    - Find multiple dual optimal extreme points
      - -Do a linear combination



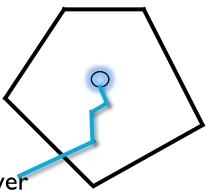


Average time	Average nb Iterations
384.4 s	72.6
389.1 s	61.0
277.9 s	37.1
	384.4 s 389.1 s



- Stabilization!
  - What to do?
  - Popular technique
    - Box penalization
  - Interior point stabilization
    - Find multiple dual optimal extreme points
      - Do a linear combination
    - Simple idea: barrier algorithm without crossover

#### **Optimal dual space**





Any Questions?

Thank you!