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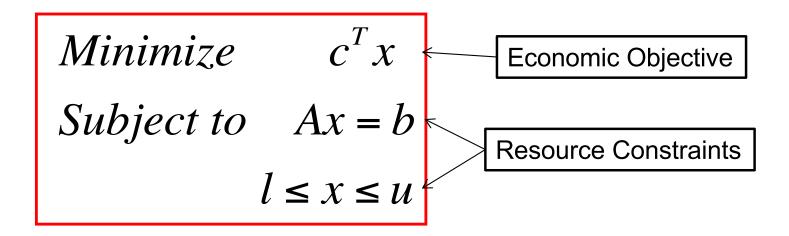
### Overview

- Linear Programming
  - Historical perspective
  - Computational progress
- Mixed Integer Programming
  - Introduction: what is MIP?
  - Solving MIPs: a bumpy landscape
  - Computational progress



## **A** Definition

A *linear program* (LP) is an optimization problem of the form





# The Early History

- 1947 George Dantzig
  - 4 Nobel Prizes in LP (Economists)
  - Invented simplex algorithm
  - First LP solved: Laderman (1947), 9 cons., 77 vars., 120 mandays.
- ▶ 1951 First computer code for solving LPs
- ▶ 1960 LP commercially viable
  - Used largely by oil companies
- ▶ 1970 MIP commercially viable
  - MPSX/370, UMPIRE



## The Decade of the 70's

#### Interest in optimization flowered

- Numerous new applications identified
  - Large scale planning applications particularly popular

#### Significant difficulties emerged

- Building application was very time consuming and very risky
  - 3-4 year development cycles
- The technology just was not ready: LPs were hard and MIP was a disaster
- ▶ Result: Disillusionment with LP and MIP.



## The Decade of the 80's

#### Mid 80's:

- There was perception was that LP software had progressed about as far as it could go – MPSX/370 and MPSIII
- BUT LP was definitely not a solved problem ... example: "Unsolvable" airline LP model with 4420 constraints, 6711 variables

#### There were several key developments

- IBM PC introduced in 1981
- Relational databases developed:
  - Separation of logical and physical allocation of data.
  - ERP systems introduced.
- Karmarkar's 1984 paper on interior-point methods



## The Decade of the 90's

- LP performance takes off
  - Primal-dual log-barrier algorithms completely reset the bar
  - Simplex algorithms unexpectedly kept pace
- Data became plentiful and accessible
  - ERP systems became commonplace
- Popular new applications begin to show that MIP could work on difficult, real-world problems
  - Airlines, Supply-Chain



# Linear Programming



401,640 constraints 1,584,000 variables

#### Solution time line (2.0 GHz Pentium 4):

Test: Went back to 1st CPLEX (1988)

• 1988 (CPLEX 1.0): Houston, 13 Nov 2002



401,640 constraints 1,584,000 variables

### Solution time line (2.0 GHz Pentium 4):

- Test: Went back to 1<sup>st</sup> CPLEX (1988)
- 1988 (CPLEX 1.0): 8.0 days (Berlin, 21 Nov)



401,640 constraints 1,584,000 variables

### Solution time line (2.0 GHz Pentium 4):

- Test: Went back to 1st CPLEX (1988)
- 1988 (CPLEX 1.0): 15.0 days (Dagstuhl, 28 Nov)



401,640 constraints 1,584,000 variables

#### Solution time line (2.0 GHz Pentium 4):

- Test: Went back to 1st CPLEX (1988)
- 1988 (CPLEX 1.0): 19.0 days (Amsterdam, 2 Dec)



401,640 constraints 1,584,000 variables

#### Solution time line (2.0 GHz Pentium 4):

Test: Went back to 1st CPLEX (1988)

• 1988 (CPLEX 1.0): 23.0 days (Houston, 6 Dec)



401,640 constraints 1,584,000 variables

### Solution time line (2.0 GHz Pentium 4):

Test: Went back to 1st CPLEX (1988)
 Speedup

• 1988 (CPLEX 1.0): 29.8 days **1x** 

• 1997 (CPLEX 5.0): 1.5 hours 480x

2003 (CPLEX 9.0): 59.1 seconds 43500x



# LP Today

- Practitioners consider LP a solved problem
- Large models can now be solved robustly and quickly
  - Regularly solve models with millions of variables and constraints



# LP Today

- However, a word of warning ...
  - Real applications still exist where LP performance is an issue
    - ~2% of MIPs are blocked by LP performance
    - Challenging pure-LP applications persist
      - Ex: Power industry (Financial Transmission-Right Auctions)
  - Challenge: Further research in LP algorithms is needed (there has been little progress since 2004)



# Mixed Integer Programming



## **A** Definition

A mixed-integer program (MIP) is an optimization problem of the form

$$Minimize c^{T}x$$

$$Subject to Ax = b$$

$$l \le x \le u$$

Subject to 
$$Ax = b$$

$$l \le x \le u$$

some or all  $x_i$  integer



### **Customer Applications**

(Q4 2011-Q3 2012)

- Accounting
- Advertising
- Agriculture
- Airlines
- ATM provisioning
- Compilers
- Defense
- Electrical power
- Energy
- Finance
- Food service
- Forestry
- Gas distribution
- Government
- Internet applications
- Logistics/supply chain
- Medical
- Mining

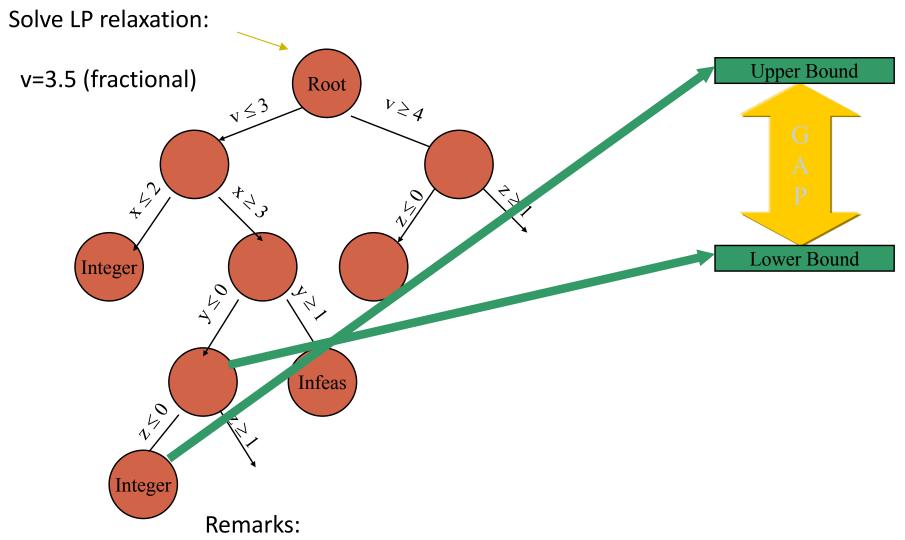
- National research labs
- Online dating
- Portfolio management
- Railways
- Recycling
- Revenue management
- Semiconductor
- Shipping
- Social networking
- Sourcing
- Sports betting
- Sports scheduling
- Statistics
- Steel Manufacturing
- Telecommunications
- Transportation
- Utilities
- Workforce Management



# Solving MIPs



### MIP solution framework: LP based Branch-and-Bound



- (1) GAP =  $0 \Rightarrow$  Proof of optimality
- (2) In practice: Often good enough to have good Solution

# A Bumpy Solution Landscape



# Example 1: LP still can be HARD

SGM: Schedule Generation Model 157323 rows, 182812 columns

- □ LP relaxation at root node:
  - 18 hours
- □ Branch−and−bound
  - 1710 nodes, first feasible
  - 3.7% gap
  - Time: 92 days!!
- MIP does not appear to be difficult: LP is a roadblock



# Example 2: MIP really is HARD

A customer model: 44 constraints, 51 variables, maximization 51 general integer variables (and no bounds)

Branch-and-bound: Initial integer solution -2186.0

Initial upper bound -1379.4

...after 1.4 days, 32,000,000 B&B nodes, 5.5 Gig tree

Integer solution and bound: UNCHANGED

What's wrong? Bad modeling. Free GIs chase each other off to infinity.



# Example 2: Here's what's wrong

Maximize
$$x + y + z$$
Subject To
 $2x + 2y \le 1$ 
 $z = 0$ 
 $x$  free  $y$  free
 $x, y$  integer

Note: This problem can be solved in several ways

- Removing z=0, objective is integral [*Presolve*]
- Euclidean reduction on the constraint [Presolve]

However: Branch-and-bound cannot solve!



# Example 3: A typical situation today - Supply-chain scheduling

### Model description:

- Weekly model, daily buckets: Objective to minimize end-of-day inventory.
- Production (single facility), inventory, shipping (trucks), wholesalers (demand known)

### Initial modeling phase

- Simplified prototype + complicating constraints (production run grouping req't, min truck constraints)
- RESULT: Couldn't get good feasible solutions.

### Decomposition approach

- Talk to current scheduling team: They first decide on "producibles" schedule. Simulate using heuristics.
- Fixed model: Fix variables and run MIP



# Supply-chain scheduling (continued): Solving the fixed model

#### CPLEX 5.0 (1997):

```
Integer optimal solution (0.0001/0): Objective = 1.5091900536e+05
Current MIP best bound = 1.5090391809e+05 (gap = 15.0873)
Solution time = 3465.73 sec. Iterations = 7885711 Nodes = 489870 (2268)
```

#### CPLEX 11.0 (2007):

```
Implied bound cuts applied: 60
Flow cuts applied: 85
Mixed integer rounding cuts applied: 41
Gomory fractional cuts applied: 29

MIP - Integer optimal solution: Objective = 1.5091900536e+05
Solution time = 0.63 sec. Iterations = 2906 Nodes = 12
```

Original model: Now solvable to optimality in ~100 seconds (20% improvement in solution quality)



# Computational History: 1950 –1998

- 1954 Dantzig, Fulkerson, S. Johnson: 42 city TSP
  - Solved to optimality using LP and cutting planes
- 1957 Gomory
  - Cutting plane algorithms
- 1960 Land, Doig; 1965 Dakin
  - B&B
- 1964–68 LP/90/94
  - First commercial application
- IBM 360 computer
  - 1974 MPSX/370
  - 1976 Sciconic
    - LP-based B&B
    - MIP became commercially viable

- 1975 1998 Good B&B remained the state-of-the-art in commercial codes, in spite of ....
  - Edmonds, polyhedral combinatorics
  - 1973 Padberg, cutting planes
  - 1973 Chvátal, revisited Gomory
  - 1974 Balas, disjunctive programming
  - 1983 Crowder, Johnson, Padberg: PIPX, pure 0/1 MIP
  - 1987 Van Roy and Wolsey: MPSARX, mixed 0/1 MIP
  - TSP, Grötschel, Padberg, ...



#### 1998 ... A New Generation of MIP Codes

- Linear programming
  - Stable, robust dual simplex
- Variable/node selection
  - Influenced by traveling salesman problem
- Primal heuristics
  - 12 different tried at root
  - Retried based upon success
- Node presolve
  - Fast, incremental bound strengthening (very similar to Constraint Programming)

- Presolve numerous small ideas
  - Probing in constraints:

$$\sum x_j \le (\sum u_j) y, y = 0/1$$
  
 $\Rightarrow x_j \le u_j y \text{ (for all j)}$ 

- Cutting planes
  - Gomory, mixed-integer rounding (MIR), knapsack covers, flow covers, cliques, GUB covers, implied bounds, zero-half cuts, path cuts



## Some Test Results

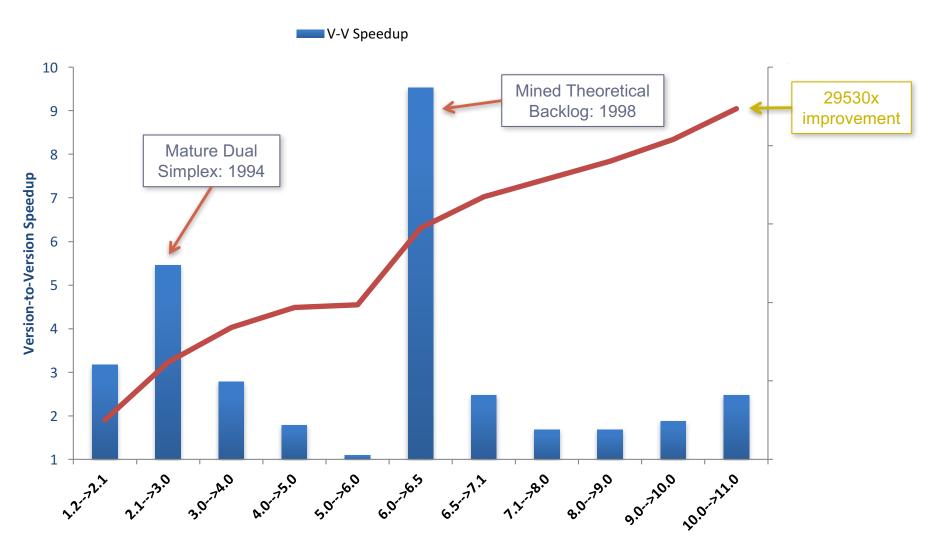
- Test set: 1852 real-world MIPs
  - Full library
    - 2791 MIPs
  - Removed:
    - 559 "Easy" MIPs
    - 348 "Duplicates"
    - 22 "Hard" LPs (0.8%)
- Parameter settings
  - Pure defaults
  - 30000 second time limit
- Versions Run
  - CPLEX 1.2 (1991) -- CPLEX 11.0 (2007)



# MIP Speedups



# CPLEX Version Performance Improvements (1991–2008)



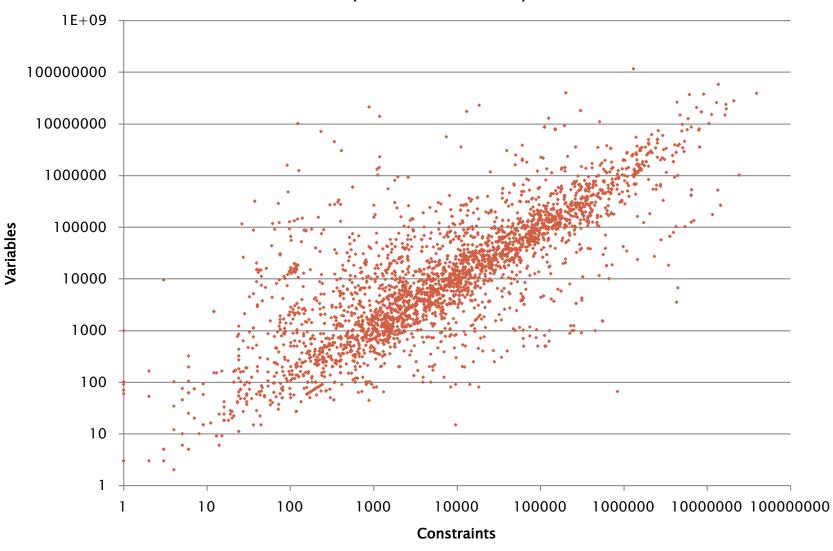
**CPLEX Version-to-Version Pairs** 

# Progress: 2009 - Present



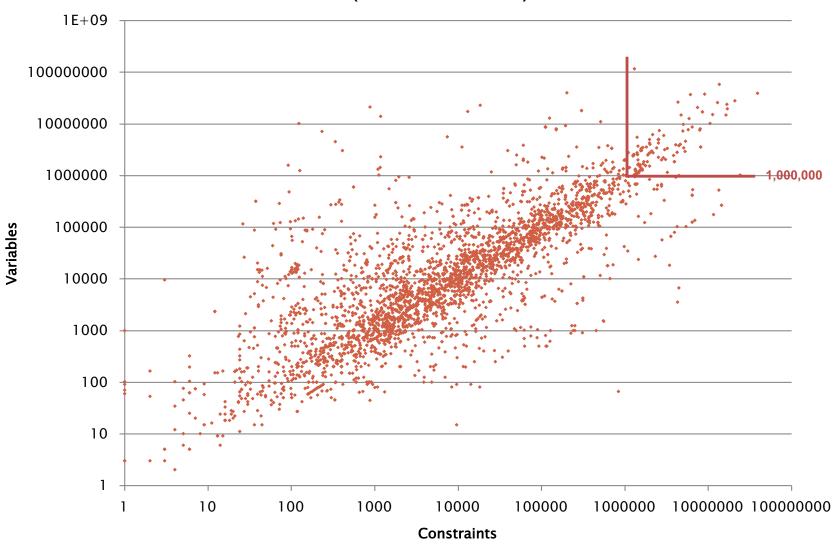
### **Gurobi MIP Library**

(3550 models)



### **Gurobi MIP Library**

(3550 models)



# MIP Speedup 2009-Present

- Starting point
  - Gurobi 1.0 & CPLEX 11.0 ~equivalent on 4-core machine
- Gurobi version-to-version improvements

```
Gurobi 1.0 -> 2.0: 2.2X
```

- Machine-independent IMPROVEMENT since 1991
  - Over 1.3 million X -- 1.8X/year



# Suppose you were given the following choices:

- Option 1: Solve a MIP with today's solution technology on a machine from 1991
- Option 2: Solve a MIP with 1991 solution technology on a machine from today

Which option should you choose?

Answer: Option 1 would be faster by a factor of approximately 300.



# Thank you

