Discrete Optimization

(at IBM's Mathematical Sciences Department)

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Outline

- ▷ Real-world optimization (and at IBM)
- Application areas
- Recent job postings
- Discrete Optimization basics
- Problems
- Computational Complexity
- Formulations
- Solution techniques: integer programming
- Branch-and-bound
- Cutting planes
- ▷ Applications
- Steel industry
- Pipelines + more

Real-world Optimization

IBM Research

IBM: 377,757 employees (end of 2015) IBM Research: 12 labs, 3000+ researchers



IBM's Math. Sciences Dept.

IBM Mathematical Sciences Department:

- \diamond 50+ years old
- \diamond 50+ people
- \diamond 50 % funding from contracts, 50% from IBM grants
- 40% of time spent on applied work \equiv need to publish 2-3 papers (or perish)
- 100% of time spent on applied work \equiv need to publish 0 papers

Discrete Optimization

Discrete optimization is the study of problems where the goal is to select a minimum cost alternative from a finite (or countable) set of alternatives.

Application areas

Airlines	route planning, crew scheduling
	revenue management
Package Delivery	vehicle routing
Trucking	route planning, vehicle routing
Transportation	network optimization
Telecommunication	network design
Shipping	route planning
Pipelines	batch scheduling, network flows
Steel Industry	cutting stock
Paper Industry	cutting stock
Finance	portfolio management
Oil & Gas	pooling
Petrochemicals	
Power generation	unit commitment, resource managem
Railways	Timetabling, crew-scheduling

American, United Air New Zealand, British Airways UPS, Fedex, USPS Schnieder Amazon AT&T Maersk CLC, CNPC Posco GSE mbH Axioma ExxonMobil SK Innovation nent BC Hydro BNSF, CSX, Belgian Railways, Deutsche Bahn, Trenitalia

Recent jobs in optimization

2016

Amazon - Operations Research Scientist

Network optimization, Linear and Integer programming - AMPL, Mosel, R, Matlab (Ph.D.)

Amazon - *Applied Scientist- Operations Research, Devices* Linear Programming, Combinatorial optimization, Integer programming - CPLEX, Gurobi, XPRESS (M.S.)

BAE Systems - *Research Engineer Planning and Control* Vehicle Routing, Network Optimization - Mathematical Programming, Control Theory (B.S./M.S./Ph.D.)

BNSF - OR & Advanced Analytics Specialist I Railroad logistics - CPLEX, Gurobi, ProModel, ARENA, Frontline Solver (M.S./Ph.D.)

Facebook - Operations Research Scientist Supply chain optimization, Inventory planning - Mathematical Programming (M.S./Ph.D.)

FedEx - Operations Research Analyst

Schedule optimization, network planning, truck routing, crew planning, facility location (M.S.)

GE - *Operations Research Specialist* Optimize railroad operations - CPLEX or Gurobi (M.S./Ph.D.)

LG Electronics USA - Applied Operations Research Lead

Demand/Inventory planning, Logistics optimization - AMPL, CPLEX (B.S.)

Modular mining - *Operations Researcher* "Optimization of operational aspects of mining" - CPLEX, Gurobi, GAMS, AMPL (M.S./Ph.D.)

Walt Disney World Resort - Decision Science Consultant Mixed-integer, non-linear, stochastic optimization or Simulation (M.S./Ph.D.)

Uber - *Operations Research Scientist* Optimize matching of riders to drivers, schedule optimization (Ph.D.)

IBM, SAS, Gurobi, Mosek, ORTEC

Problems

Knapsack Problem



Maximize the value of items packed in a knapsack while not exceeding its capacity

Knapsack Problem



Cutting stock

Pack items into as few identical knapsacks as possible: Used in steel, paper industry)



Traveling Salesman Problem

TSP: Minimize distance traveled while visiting a collection of cities and returning to the starting point.



33-city TSP instance from a 1962 Procter and Gamble competition (\$10,000 prize won by Gerald Thompson of CMU)



10-city instance



(n-1)! = 362,880 possible tours

10-city instance

	0	1	2	3	4	5	6	7	8	9
0 Chicago	0									
1 Erie	449	0								
2 Chattanooga	618	787	0							
3 Kansas City	504	937	722	0						
4 Lincoln	529	1004	950	219	0					
5 Wichita	805	1132	842	195	256	0				
6 Amarillo	1181	1441	1080	563	624	368	0			
7 Butte	1538	2045	2078	1378	1229	1382	1319	0		
8 Boise	1716	2165	2217	1422	1244	1375	1262	483	0	
9 Reno	2065	2514	2355	1673	1570	1507	1320	842	432	0

10-city instance: solutions

Tours of length 6633 and 6514 miles





Shortest tour: 0, 1, 2, 3, 5, 6, 9, 8, 7, 4 Shortest tour length: 6514



Minimize distance traveled by trucks at a depot delivering to a set of customers within prescribed time windows (used in package delivery by Fedex, USPS etc.) 2014 survey in OR-MS Magazine lists 15+ vendors of VRP software.

Min-max vehicle routing







1996 Whizzkids challenge

▷ 5000 Dutch Guilders prize sponsored by CMG

Winners: Hemel, van Erk, Jenniskens (U. Eindhoven students)
Max path length of 1183
Local search techniques, 15,000 hours of computing time.

Optimal solution? Lower bound of 1160 given by Hurkens '97.

Integer programming





Integer Quadratic programming

min $2x^2 + 5y^2 + 6xy + 3x$ subject to $.9x + y \ge 1.5, x + 3.1y \ge 2.4$ $0 \le x \le 3.5, 0 \le y \le 3.3, x, y$ integral



Computational Complexity

NP-completeness

The problem of determining if there exists a TSP tour of length less than k is NP-complete.



Running time growth

▷ Traveling salesman problem: $O(n^2 2^n)$ algorithm by Held and Karp ▷ Shortest path problem: $O(n^2)$ algorithm by Djikstra

function	5	10	30	64
n^2	25	100	900	4096
n ² log n	58.0	332.2	4,416.2	24, 576
2 ⁿ	32	1024	1,073,741,824	18, 446, 744, 073, 709, 551, 616
$ 1.1^n$	1.6	2.6	17.4	445.8

Important: For real-life applications, the data/problem size are restricted.

Time taken by Pisinger's MINKNAP algorithm on knapsack instances with n items and item weights chosen uniformly at random from $1, \ldots, R$.

	U	ncorrela	ted	strongly correlated			
n/R	100	1000	10000	100	1000	10000	
100	.002	.002	.002	.002	.002	.076	
1000	.002	.002	.003	.019	.078	.172	
10000	.004	.005	.010	.050	1.19	25.2	

Formulations

0-1 Knapsack formulations

Profits p_i and weights w_i are assumed to nonnegative

integer program:

Maximize
$$p_1 x_1 + p_2 x_2 + \ldots + p_n x_n$$

s.t. $w_1 x_1 + w_2 x_2 + \ldots + w_n x_n \le c$
 $x_1, x_2, \ldots, x_n \in \{0, 1\}.$

For *unbounded knapsack* replace {0, 1} by {integers} above.

nonlinear integer program:

Maximize
$$p_1 x_1 + p_2 x_2 + \ldots + p_n x_n$$

s.t. $w_1 x_1^2 + w_2 x_2^2 + \ldots w_n x_n^2 \le c$
 $x_1, x_2, \ldots, x_n \in \{0, 1\}.$

0-1 Knapsack relaxations

Maximize	$2x_1 + x_2$	Maximize	$2x_1 + x_2$
s.t.	$x_1 + x_2 \le 1$	s.t.	$x_1^2 + x_2^2 \le 1$
	$x_1, x_2 \in \{0, 1\}.$		$x_1, x_2 \in \{0, 1\}.$

Maximize	$2x_1 + x_2$	Maximize	$2x_1 + x_2$
s.t.	$x_1 + x_2 \le 1$	s.t.	$x_1^2 + x_2^2 \le 1$
	x_1 , $x_2 \in [0, 1]$.		$x_1, x_2 \in [0, 1]$





Solution techniques

Basic optimization

Minimize f(x) for x in some domain



Optimality conditions



Necessary condition for optimality of x is f'(x) = 0. f''(x) > 0 is sufficient condition for local optimality. For convex functions, first condition is sufficient.

For constrained optimization, KKT conditions are necessary (Kuhn, Tucker '54, Karush '39).

Integer programming





LP relaxation





LP relaxation + branching

min 5x + 8y subject to $.9x + y \ge 1.5, x + 3.1y \ge 2.4$ $0 \le x \le 3.5, 0 \le y \le 3.3$

min 5x + 8y subject to $.9x + y \ge 1.5, x + 3.1y \ge 2.4$ $0 \le x \le 1, 0 \le y \le 3.3$ min 5x + 8y subject to $.9x + y \ge 1.5, x + 3.1y \ge 2.4$ $2 \le x \le 3.5, 0 \le y \le 3.3$

Branch and bound



		ср	lex-log2.txt			
Problem 'pp08a	' read.					
Reduced MIP ha Reduced MIP ha	s 133 rows, 234 s 64 binaries,	columns 0 genera	, and 468 nor lls, 0 SOSs, a	nzeros. and 0 indicato	ors.	
Nodes Node Left	0bjective	IInf Be	est Integer	Cuts/ Best Bound	ItCnt	Gap
* 0+ 0 0 0 * 0+ 0 * 0+ 0	2748.3452	51	27080.0000 27080.0000 14300.0000 7950.0000	2748.3452 2748.3452 2748.3452	77 77 77 77	 89.85% 80.78% 65.43%
0 2 Elapsed real t * 100+ 94	2748.3452 ime = 0.03 se	51 c. (tree	7950.0000 e size = 0.00 7860.0000	2748.3452 D MB, solution 2848.3452	5 = 3) 428	65.43% 63.76%
* 100+ 90 2862 2111 6557 5339 * 10017+ 8320 * 10017+ 8067	6556.5595 6788.4524	28 21	7640.0000 7640.0000 7640.0000 7630.0000 7520.0000	2848.3452 3981.3452 4254.2976 4369.3452 4369.3452	428 9387 20447 30879 30879	62.72% 47.89% 44.32% 42.73% 41.90%
* 10017+ 8047 * 10017+ 7947 10017 7949	7152.1667	16	7510.0000 7480.0000 7480.0000	4369.3452 4369.3452 4369.3452	30879 30879 30879	41.82% 41.59% 41.59%
467260 381944 Elapsed real t	6279.9524 ime = 76.80 se	23 c. (tree	7480.0000 size = 86.82	5330.2500 2 мв, solution	1336479 s = 9)	28.74%
488008 398616 508767 415262 529510 431893 550267 448498 570955 465047	6870.4881 7018.3810 5359.7738 5819.7024 7091.7738	16 21 26 30 13	7480.0000 7480.0000 7480.0000 7480.0000 7480.0000	5340.1310 5350.3452 5359.7738 5368.3929 5377.4405	1393871 1451784 1509653 1567040 1624524	28.61% 28.47% 28.35% 28.23% 28.11%
760995 616110 778020 629628 794094 642371 811975 656559	6726.4405 6542.1548 6215.4881 cutoff	24 30 25	7480.0000 7480.0000 7480.0000 7480.0000	5445.6548 5451.3214 5456.2024 5461.4405	2152219 2199840 2244463 2294026	27.20% 27.12% 27.06% 26.99%
829297 670288 846366 683716 Elapsed real t	6740.9167 6716.6786 ime = 143.55 se	28 22 c. (tree	7480.0000 7480.0000 e size = 155.1	5466.6786 5471.6786 11 MB, solutio	2342402 2389544 ons = 9)	26.92% 26.85%

Cutting planes

cutting plane: an inequality satisfied by integral solutions of linear inequalities.

min 5x + 8y subject to $.9x + y \ge 1.5, x + 3.1y \ge 2.4$ $0 \le x \le 3.5, 0 \le y \le 3.3, x, y$ integral



Gomory-Chvátal cutting planes (cuts)

$$x \le 3.5 \Rightarrow x \le 3$$
$$y \le 3.3 \Rightarrow y \le 3$$

$$(.9x + y \ge 1.5) + (.1x \ge 0) \rightarrow$$

 $x + y \ge 1.5 \Rightarrow x + y \ge 2$

$$(x + y \ge 2) \times .6 + (x + 3.1y \ge 2.4) \times .4 \rightarrow$$
$$x + 1.84y \ge 2.16 \rightarrow$$
$$x + 2y \ge 2.16 \Rightarrow x + 2y \ge 3.$$

Every integer program can be solved by Gomory-Chvátal cuts (Gomory '60), though it may take exponential time in the worst case (Pudlák '97).

Reduced MIP has 133 rows, 234 columns, and 468 nonzeros. Reduced MIP has 64 binaries, 0 generals, 0 SOSs, and 0 indicators. Nodes Cuts/ Objective IInf Best Integer Node Left Best Bound ItCnt Gap * 0 +0 27080.0000 77 _ _ _ 2748.3452 51 2748.3452 89.85% 0 0 27080.0000 77 * 0 77 0 +2748.3452 14300.0000 80.78% 0 0 5046.0422 48 14300.0000 Cuts: 133 153 64.71% 6749.5837 52.80% 0 0 24 14300.0000 Cuts: 130 265 * 0 10650.0000 0+6749.5837 265 36.62% 0 0 7099.1233 27 10650.0000 Cuts: 53 327 33.34% 0 0 7171.1837 28 10650.0000 Cuts: 35 356 32.66% * 0 0 +7540.0000 7171.1837 356 4.89% 0 0 7176.2716 31 7540.0000 370 4.82% Cuts: 19 33 7540.0000 0 0 7187.8155 Cuts: 20 388 4.67% 0 0 28 7540.0000 7188.4198 Cuts: 4 398 4.66% 0 7189.5182 30 0 7540.0000 Cuts: 9 409 4.65% 0 0 7189.5877 30 Flowcuts: 5 4.65% 7540.0000 413 0 0 26 7189.9535 7540.0000 Flowcuts: 2 420 4.64% 0 2 7189.9535 26 7540.0000 7190.0161 420 4.64% Elapsed real time = 0.27 sec. (tree size = 0.00 MB, solutions = 4) 7530.0000 1733 50 +40 7218.8496 4.13% * 55 44 integral 0 7520.0000 7218.8496 4.00% 1783 * 60 +45 7490.0000 7218.8496 1892 3.62% * 38 2.71% 60 +7420.0000 7218.8496 1892 * 53 2.18% 110 +7400.0000 7238.6753 2712 * 210 64 integral 0 7350.0000 7255.3139 4760 1.29% Implied bound cuts applied: 1 Flow cuts applied: 149

Flow path cuts applied: 23 Multi commodity flow cuts applied: 5 Gomory fractional cuts applied: 34 Total (root+branch&cut) = 0.95 sec.

cplex-log.txt

Problem 'pp08a' read.

cplex_speedups Chart 4



Applications

Steel industry application

Context: Large steel plant (3 million tons of plates/year \approx 10,000 tons/day) in East Asia moving from a producer-centric model to a customer-centric model

Goal: Optimization tool to generate a production design – a detailed desciption of production steps and related intermediate products

Timeline: 1.5 years (5 man years on optimization, 25 man years on databases/GUI/analysis) (joint work with J. Kalagnanam, C. Reddy, M. Trumbo)

Manufacturing process



Consulting Issues

◊ 2+ research man years spent defining problem (high complexity)

- Very large number of constraints including objectives masked as constraints
- 500+ pages of specifications: scope of problem not known at contract signing

♦ High level problem has non-linearities

♦ Software/data issues - 1000+ files

♦ 30 minutes of computing time allowed

- 100+ complex cutting stock problems with up to 2000 orders solved via integer programming column generation

Pipeline management

Schedule injections of batches of oil on a pipeline network while minimizing interface costs, delays, and power costs and satisfying tank constraints

(joint work with V. Austel, O. Günlük, P. Rimshnick, B. Schieber)

A pipeline network has many pipelines, each with multiple segments, each of which can run at multiple 'natural rates'.

Timeline: 2.5 years (10+ man years on optimization

Inputs to Batch Sequencing Problem



Batch sequencing

When the pipeline consists of single segment, the cost of a batch sequence depends only on interface costs of adjacent batch pairs: batch sequencing reduces to the Asymmetric TSP problem.

	0	1	2	3	4	5	6	7	8	9
0 Chicago	0									
1 Erie	449	0								
2 Chattanooga	618	787	0							
3 Kansas City	504	937	722	0						
4 Lincoln	529	1004	950	219	0					
5 Wichita	805	1132	842	195	256	0				
÷										

Vehicle routing application

Context: Food distribution company in North America trying to improve delivery to customers within desired time windows, while minimizing travel costs.

VRPTW with driver preferences



Customers have preferred drivers; penalize for delivery by non-preferred driver.

♦ 200-300 customers, 20-30 routes per shift, 3-6 shifts per day

 \diamond Create preference relationships between \approx 200 drivers and 1000 customers (joint work with O. Günlük, G. Sorkin)



Graphic Route Comparison



Comparison of route characteristics – Changing Input Parameters and Penalties directly impacts optimizer solution.

Facility location problem



Related to Fermat-Weber problem

Machine learning application

▷ Insurance company wants to answer a long list of customer questions, but has a budget for only 500 answers (Dmitry Malioutov).



▷ The problem is an "active learning" problem: try to optimize which questions to answer.

▷ Balance "information gain" vs. "diversity" for each answered question.

Inputs:

1) Each node/question has a notion of how much additional information it will add by providing a human answer – this is the node cost.

2) The similarity of each question to other questions: there is no point in answering the same question 20 times, so it's great to have a diverse set of questions to ask humans to answer.

DWave Quantum Computer

DWave: An adiabatic quantum computer performing "quantum annealing".

▷ A special-purpose analog machine employing "flux qubits" arranged in a Chimera graph structure solving the Ising Model Problem. DWave does not guarantee optimality.

DWave experiments

McGeoch and Wang: Experimental Evaluation of an adiabatic quantum system for combinatorial optimization, *ACM Conference on Computing Frontiers* 2013.

In horserace terms, QA dominates on the Chimera-structure QUBO problems: at the largest problem size n = 439, CPLEX (best among the software solvers), returns comparable results running about 3600 times slower than the hardware. On the W2SAT problems, Blackbox, AK, and TABU

▷ DWave Two takes half a second versus half an hour for CPLEX 12.3. on quadratic unconstrained boolean optimization (QUBO) problems defined on a Chimera graph

New York Times:

MAY 16, 2013, 5:00 AM | 📮 30 Comments

Google Buys a Quantum Computer

By QUENTIN HARDY

quantum physics. Their quantum computer, which performs complex calculations thousands of times faster than existing supercomputers, is expected to be in active use in the third quarter of this year. New York Times (Nov 14,2013):

This year, Google and a corporation associated with NASA acquired for study an experimental computer that appears to make use of quantum properties to deliver results sometimes 3,600 times faster than traditional supercomputers. The maker of the quantum computer, D-Wave Systems of Burnaby, British Columbia, counts Mr. Bezos as an investor.

Chimera graphs

Chimera graph C_n : $8n^2$ nodes with $n^2 K_{4,4}$ graphs arranged in a $n \times n$ grid.



 C_4

QUBO problem

The Ising model problem is equivalent to the QUBO problem.

▷ The quadratic unconstrained boolean optimization problem (QUBO) problem: Given an $n \times n$ matrix Q:

Min
$$\sum_{i,j} Q_{ij} x_i x_j$$
 subject to $x \in \{0, 1\}^n$. (1)

QUBO problems

McGeoch and Wang solve QUBO-miqp using the CPLEX MIQP solver

The CPLEX MIQP solver does branch-and-bound based on the QP relaxation:

Min
$$\sum_{i,j} Q_{ij} x_i x_j$$
 subject to $x \in [0, 1]^n$. (2)

QUBO problems

QUBO-milp: Classical mixed-integer linear programming formulation (assume Q is upper triangular):

$$\begin{array}{ll} \operatorname{Min} \ \sum_{i < j} Q_{ij} z_{ij} + \sum_{i=1}^{n} Q_{ii} x_{i} & (3) \\ & \text{subject to} & \\ x \in \{0, 1\}^{n}, & (4) \\ & z_{ij} \leq x_{i} & \forall i < j, & (5) \\ & z_{ij} \leq x_{j} & \forall i < j, & (5) \\ & x_{i} + x_{j} - z_{ij} \leq 1 & \forall i < j, & (6) \\ & x_{i} + x_{j} - z_{ij} \leq 1 & \forall i < j, & (7) \\ & z_{ij} \geq 0 & \forall i < j. & (8) \end{array}$$

For any fixed *i*, *j*, the constraints (5)-(8) are called Fortet inequalities or McCormick inequalities and force z_{ij} to equal $x_i x_j$ when $x_i, x_j \in \{0, 1\}$.

Experiments

▷ CPLEX 12.3/QUBO-MILP takes 93.8 seconds in the worst case and not half an hour: Dash, Puget '14

▷ Simulated annealing heuristic takes 0.02 seconds on 512 node instances: Boixo, Ronnow, Isacker, Wang, Wecker, Lidar, Martinis, Troyer '13.

▷ Specialized heuristic takes 0.01 seconds on 439 node instances: Selby '13.

Conclusions

Many real-life optimization problems can be modeled as instances of NP-hard problems. However, as the data and problem sizes are restricted, such problems can often be solved with customized techniques.

▷ Linear-integer programming is the most widely used optimization tool in practical applications, but some important problems (e.g., portfolio optimization) are modeled as nonlinear (quadratic) integer programs.

▷ Linear constraints are more common in combinatorial problems, whereas nonlinear constraints are more common in systems where the physics is important.