# Challenging combinatorial problems 

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## Outline

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- recall some challenging combinatorial problems from previous lectures


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- introduce a couple of new ones


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- recall some challenging combinatorial problems from previous lectures
- introduce a couple of new ones
- difficulty: worth a variable number of bottles of wine (scale: from 1 to $\infty$ ).


## Outline

(1) Combinatorial models in manufacturing

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## Outline

(1) Combinatorial models in manufacturing
(2) Boolean functions and games

## Outline

(9) Combinatorial models in manufacturing

- Tool management
- Robotic cells


## Outline

## (1) Combinatorial models in manufacturing - Tool management

## Setup minimization

## Tool setup in automated manufacturing:

- limited size of the tool magazine (say, 10 to 120 tools)


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- many more tools may be stored in a central storage area
- transferred to the machines as required
- costly, slow, error-prone operations

One-machine scheduling with tooling decisions:
Simultaneously

- sequence parts to be processed and
- allocate tools required to the machine so as to minimize tool setup costs.


## Setup minimization

Various models for setup minimization.

## Common data

- M: number of tools;
- $N$ : number of parts;
- $A: M \times N$ tool-part matrix:

$$
a_{i j}=1 \text { if part } j \text { requires tool } i, 0 \text { otherwise; }
$$

- $C$ : capacity of the tool magazine ( = number of tool slots)


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## Feasible batch

A batch of parts is feasible if it can be carried out without tool switches, i.e., if it requires at most $C$ tools.

## Example

Capacity: $C=3$

## Parts

Tools |  |  | $P_{1}$ | $P_{2}$ | $P_{3}$ | $P_{4}$ | $P_{5}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $T_{1}$ | 1 | 0 | 1 | 0 | 1 |
|  | $T_{2}$ | 1 | 0 | 0 | 1 | 0 |
|  | $T_{3}$ | 0 | 1 | 1 | 1 | 0 |
|  | $T_{4}$ | 0 | 1 | 0 | 0 | 1 |

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Find a feasible batch of maximum cardinality.

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Find a largest subset of columns of the tool-part incidence matrix such that the submatrix induced by this subset has at most $C$ nonzero rows.

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Find a feasible batch of maximum cardinality.

Equivalently:

## Batch selection

Find a largest subset of columns of the tool-part incidence matrix such that the submatrix induced by this subset has at most $C$ nonzero rows.
or...

## Batch selection

Given a hypergraph, find a subset of $C$ vertices that contains the largest possible number of hyperedges.

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## Pseudo-Boolean formulation

- define : $x_{i}=1$ if tool $i$ is selected, $x_{i}=0$ otherwise
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- equivalently: part $j$ can be processed if and only if $\prod_{i: a_{j i}=1} x_{i}=1$
So:


## Nonlinear knapsack

Batch selection is equivalent to the nonlinear (supermodular) knapsack problem
$\max \sum_{j=1}^{N} \prod_{i: a_{j i}=1} x_{i}$
subject to $\sum_{i=1}^{M} x_{i} \leq C, \quad\left(x_{1}, \ldots, x_{M}\right) \in\{0,1\}^{M}$

## Complexity

## Theorem <br> Batch selection is NP-hard.

Generalization of maximum clique.

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## Theorem

Batch selection is NP-hard.

Generalization of maximum clique.
Many papers on this problem:

- integer programming
- heuristics
- special "graphical" case
- subproblem for part grouping problem: partition parts into small number of feasible batches (minimize setups).


## Worst-case ratio

From a theoretical point of view, one may ask:

## Worst-case ratio

What is the (theoretical) worst-case ratio of heuristics for the batch selection problem, where:

$$
w c r=\frac{\text { optimal value }}{\text { heuristic value }} ?
$$

## Analysis

Crama and van de Klundert (1999) proved:

## Theorem

If there is a polynomial-time approximation algorithm with constant worst-case ratio for batch selection, then there is also a polynomial-time approximation scheme for this problem.
... meaning roughly that the optimal value can be approximated arbitrarily closely in polynomial time.

## Conjectures

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## Outline

(1) Combinatorial models in manufacturing

- Tool management
- Robotic cells
- Thalization

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## Circular robotic cell



## Robotic cell flowshops

- $m$ machines in line (or on a circle), without buffer space: $M_{1}, M_{2}, \ldots, M_{m}$
- loading station $M_{0}$ and unloading station $M_{m+1}$
- set of parts to be produced by the line
- a unique robot loads and unloads the parts


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- set of parts to be produced by the line
- a unique robot loads and unloads the parts


## Robotic cell scheduling

Determine

- a sequence of parts,
- a robot activity sequence,
- a production schedule (start/end times),
- so as to minimize cycle time (maximize throughput).


## Assumptions

We concentrate here on:

- repetitive production of identical parts
- no intermediate buffers
- additive robot travel times.


## 1-Unit cycles

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A 1-unit cycle is a sequence of activities which unloads exactly one part in the output buffer and which returns the cell to its initial state.
(In particular, every activity is performed exactly once and the cycle can be repeated indefinitely.)

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(In particular, every activity is performed exactly once and the cycle can be repeated indefinitely.)
Crama and van de Klundert (1997) proved:

## Theorem

For a robotic cell with $m$ machines, a 1-unit cycle that minimizes the average cycle time can be computed in $O\left(\mathrm{~m}^{3}\right)$ time.

## Optimality of 1-unit cycles

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## k-Unit cycles

A $k$-unit cycle is a sequence of activities which unloads exactly $k$ parts in the output buffer and which returns the cell to its initial state.

Note: For some $k$, some $k$-unit cycle is optimal.

## Open question

Main open question:
Complexity
What is the complexity of computing an optimal (cyclic) robot move sequence?

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(2) Boolean functions and games

- Dualization
- Threshold functions and weighted majority games


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## Definitions

## Recall

## Boolean functions

A Boolean function is a mapping $\varphi:\{0,1\}^{n} \rightarrow\{0,1\}$. Function $\varphi$ is positive (monotone, isotone) if

$$
X \leq Y \Rightarrow \varphi(X) \leq \varphi(Y) .
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## Definitions

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$$

## Set functions:

Boolean functions on $\{0,1\}^{n}$ can also be viewed as set functions, that is, functions defined on subsets of $\{1,2, \ldots, n\}$.

## Example

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $S$ | $\varphi$ |
| :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 0 | $\emptyset$ | 0 |
| 0 | 0 | 1 | $\{3\}$ | 1 |
| 0 | 1 | 0 | $\{2\}$ | 0 |
| 0 | 1 | 1 | $\{2,3\}$ | 1 |
| 1 | 0 | 0 | $\{1\}$ | 0 |
| 1 | 0 | 1 | $\{1,3\}$ | 1 |
| 1 | 1 | 0 | $\{1,2\}$ | 1 |
| 1 | 1 | 1 | $\{1,2,3\}$ | 1 |

## Simple games

- A positive Boolean function $\varphi$ defines a simple game or voting game.
- Interpretation: $\varphi$ describes the voting rule which is adopted by the players when a decision is to be made.
- If $S$ is a subset of players, then $\varphi(S)$ is the outcome of the voting process when all players in $S$ say "Yes".
- Positivity means:

$$
S \subseteq T \Rightarrow \varphi(S) \leq \varphi(T)
$$



## Mimimal true points

- A positive Boolean function $\varphi$, or a simple game, is completely defined by the list of its mimimal true points, that is, minimal subsets of players $S_{1}, S_{2}, \ldots, S_{m}$ such that $\varphi\left(S_{i}\right)=1$ for $i=1,2, \ldots, m$.


## Example

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $S$ | $\varphi$ | MTP |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 0 | $\emptyset$ | 0 |  |
| 0 | 0 | 1 | $\{3\}$ | 1 | $S_{1}$ |
| 0 | 1 | 0 | $\{2\}$ | 0 |  |
| 0 | 1 | 1 | $\{2,3\}$ | 1 |  |
| 1 | 0 | 0 | $\{1\}$ | 0 |  |
| 1 | 0 | 1 | $\{1,3\}$ | 1 |  |
| 1 | 1 | 0 | $\{1,2\}$ | 1 | $S_{2}$ |
| 1 | 1 | 1 | $\{1,2,3\}$ | 1 |  |

## Maximal false points

- A positive Boolean function $\varphi$, or a simple game, is completely defined by the list of its mimimal true points, that is, minimal subsets of players $S_{1}, S_{2}, \ldots, S_{m}$ such that $\varphi\left(S_{i}\right)=1$ for $i=1,2, \ldots, m$.
- Similarly, $\varphi$ is completely defined by the list of its maximal false points, that is, maximal subsets of players $T_{1}, T_{2}, \ldots, T_{k}$ such that $\varphi\left(T_{j}\right)=0$ for $j=1,2, \ldots, k$.


## Example

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $S$ | $\varphi$ | MTP | MFP |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 0 | $\emptyset$ | 0 |  |  |
| 0 | 0 | 1 | $\{3\}$ | 1 | $S_{1}$ |  |
| 0 | 1 | 0 | $\{2\}$ | 0 |  | $T_{1}$ |
| 0 | 1 | 1 | $\{2,3\}$ | 1 |  |  |
| 1 | 0 | 0 | $\{1\}$ | 0 |  | $T_{2}$ |
| 1 | 0 | 1 | $\{1,3\}$ | 1 |  |  |
| 1 | 1 | 0 | $\{1,2\}$ | 1 | $S_{2}$ |  |
| 1 | 1 | 1 | $\{1,2,3\}$ | 1 |  |  |

## Dualization

A fundamental algorithmic problem:

## Dualization

- Input: the list of minimal true points of a positive Boolean function.
- Output: the list of maximal false points of the function. (or conversely)

Problem investigated in Boolean theory, game theory, integer programming, electrical engineering, artificial intelligence, reliability, combinatorics, etc.


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- all minimal transversals of a hypergraph $(V, E)$,
$E=\left(E_{1}, \ldots, E_{m}\right), E_{i} \subseteq V$ (in particular: all maximal stable
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## Dualization

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- all minimal transversals of a hypergraph $(V, E)$,
$E=\left(E_{1}, \ldots, E_{m}\right), E_{i} \subseteq V$ (in particular: all maximal stable
sets of a graph);
- all minimal solutions of a set covering problem:

$$
\begin{aligned}
& \sum_{j \in E_{i}} x_{j} \geq 1(i=1, \ldots, m) \\
& x_{j} \in\{0,1\}(j=1, \ldots, n)
\end{aligned}
$$

## Complexity

Note: the output is uniquely defined, but its size can be exponentially large in the size of the input.

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(Lawler, Lenstra, Rinnooy Kan 1980; Johnson, Papadimitriou, Yannakakis 1988; Bioch, Ibaraki 1995; etc.)
Can positive Boolean functions be dualized in total polynomial time, that is, in time polynomial in the combined size of the input and of the output?

## Equivalent problem

Dualization is "polynomially equivalent" to the problem:

## Test Dual

- Input: the MTPs of a Boolean function $\varphi$, and a list $L$ of points.
- Question: is $L$ the list of MFPs of $\varphi$ ?


## Equivalent problem

Dualization is "polynomially equivalent" to the problem:

## Test Dual

- Input: the MTPs of a Boolean function $\varphi$, and a list $L$ of points.
- Question: is $L$ the list of MFPs of $\varphi$ ?
- Dualization can be solved in total polynomial time if and only if Test Dual can be solved in polynomial time.
- Test Dual does not require exponential outputs.


## Quasi-polynomial algorithm

Fredman and Khachiyan have shown

## Fredman and Khachiyan (1996)

Dualization can be solved in time $O\left(m^{\log m}\right)$, where $m$ is the combined size of the input and of the output of the problem.

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Dualization can be solved in time $O\left(m^{\log m}\right)$, where $m$ is the combined size of the input and of the output of the problem.

- Several generalizations of this result have been obtained by Boros, Elbassioni, Gurvich, Khachiyan, Makino, etc.
- But the central questions remain open:


## Open problems

## Complexity of Dualization

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## Outline

## - Tool management - Robotic cells

(2) Boolean functions and games

- Threshold functions and weighted majority games


## Weighted majority games

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In Boolean theory, a weighted majority game is called a threshold function.

## Example



## Example



## Applications

Numerous applications:

- game theory (weighted voting)
- electrical engineering (gates)
- optimization (knapsack)
- neural networks (perceptrons)
- databases (concurrent access)
- etc.


## Threshold recognition

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## Peled and Simeone (1985)

Threshold recognition can be solved in polynomial time.

## Generic approach

## Observations:

- every threshold function $\varphi$ is regular: up to a permutation of its variables, $\varphi(\ldots 0 \ldots 1 \ldots) \leq \varphi(\ldots 1 \ldots 0 \ldots)$


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Observations:

- every threshold function $\varphi$ is regular: up to a permutation of its variables, $\varphi(\ldots 0 \ldots 1 \ldots) \leq \varphi(\ldots 1 \ldots 0 \ldots)$
- regular functions can be recognized and dualized in polynomial time (Peled-Simeone 1985, Crama 1989, etc.)
- recall: dualizing amounts to generating all maximal 0 s from all minimal 1s.


## Example



## Generic approach

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- solve the linear programming problem (in $w_{1}, \ldots, w_{n}$ ):

$$
\begin{array}{ll}
w_{1} x_{1}+w_{2} x_{2}+\ldots+w_{n} x_{n} \leq q & \text { if } \varphi\left(x_{1}, \ldots, x_{n}\right)=0 \\
w_{1} x_{1}+w_{2} x_{2}+\ldots+w_{n} x_{n}>q & \text { if } \varphi\left(x_{1}, \ldots, x_{n}\right)=1
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\end{array}
$$

## Complexity

- $O\left(n^{2} m\right)$ to test regularity and to dualize
- complexity of linear programming for separation


## Open problem

## Purely combinatorial recognition procedure

Can we avoid to solve an LP in order to recognize threshold functions?

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Can we avoid to solve an LP in order to recognize threshold functions?

- Some failed attempts in that direction in the 60's (Chow, Winder, Dertouzos, etc.)
- Question could be taken up again in the light of advances in complexity theory and optimization.
- Recent attempts by Smaus (incomplete?)


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## Purely combinatorial recognition procedure

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## Conclusion

Combinatorial Models and Complexity in Management Science

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- Many more to be found in
Y. Crama and P.L. Hammer, Boolean Functions: Theory, Algorithms, and Applications, Cambridge University Press, New York, to appear.
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## Conclusion

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Thank you for your presence and for your attention!!


