

# Large-Scale Optimization and Logical Inference

John Hooker  
Carnegie Mellon University

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University College Cork

# Research Theme

- Large-scale **optimization** and **logical inference**.
  - Optimization on large datasets.
  - Extraction of information from large datasets.
  - Application to industry problems.

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  - Optimization on large datasets.
  - Extraction of information from large datasets.
  - Application to industry problems.
- Why combine these?

# Research Theme

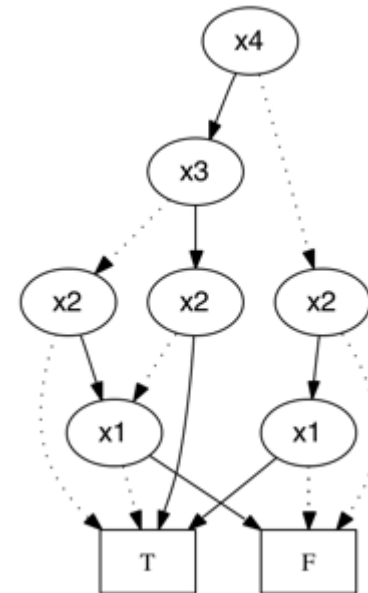
- ...to exploit **underlying unity** of optimization and logical inference
  - Both are forms of **projection**.
  - Also, combine **optimization** and **constraint programming**

# Research Streams

- Use **decision diagrams** for optimization and constraint programming.
  - Also for postoptimality analysis.
- Use **logic-based Benders decomposition** for optimization and inference
  - Computes a **projection**.
  - Combines integer programming and constraint programming.
- Use **optimization methods** for logical inference.
  - Probability logic, belief logics, etc.

# Decision Diagrams

- Graphical encoding of a boolean function
  - Historically used for circuit design & verification
  - Adapt to optimization and constraint programming
    - T. Hadžić and JH (2007)



# Decision Diagrams

- Collaborators...
  - Henrik Andersen
  - David Bergman
  - André Ciré
  - **Tarik Hadžić (now at UTRC, Cork)**
  - Samid Hoda
  - Willem-Jan van Hoeve
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\*2014 *Doctoral Thesis Award*, Assoc. for Constraint Programming

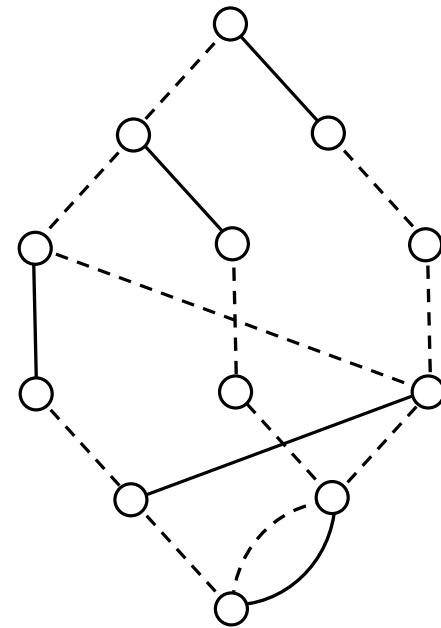
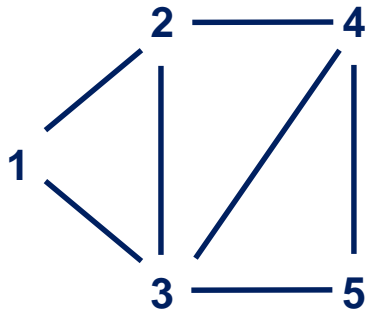
\*\*2014 *Best Student Paper Award*, INFORMS Computing Society



# Decision Diagrams

Example:  
Stable set problem

Find max-weight subset  
of nonadjacent vertices



$x_1$

$x_2$

$x_3$

$x_4$

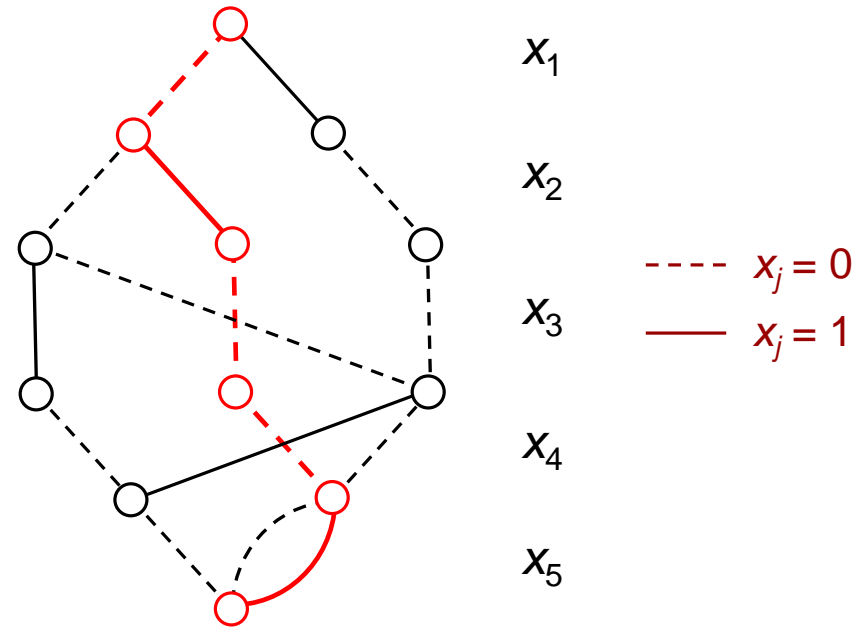
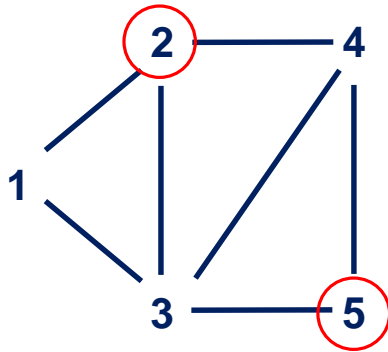
$x_5$

-----  $x_j = 0$   
———  $x_j = 1$

# Decision Diagrams

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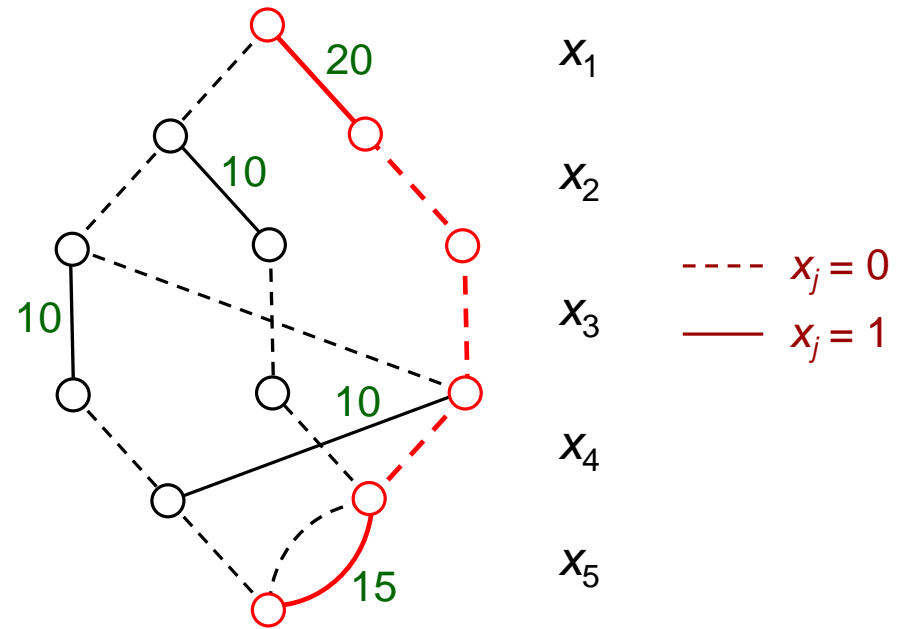
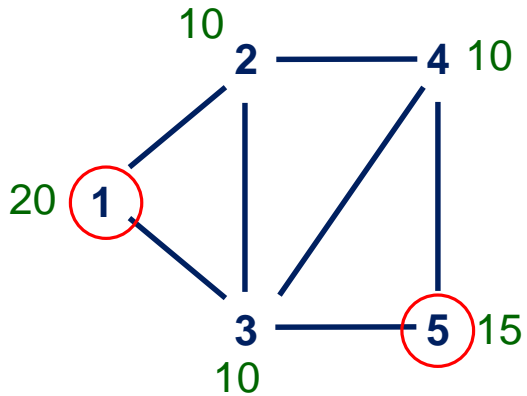


Each path corresponds to a feasible solution.

# Decision Diagrams

Example:  
Stable set problem

Find max-weight subset  
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Longest path corresponds to an optimal solution.

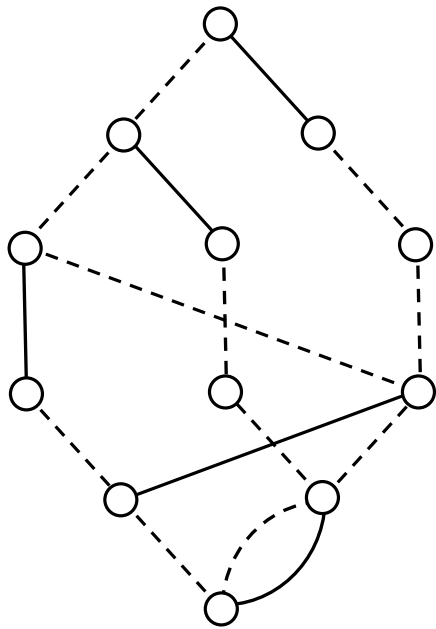
# Decision Diagrams

- Key idea: Use **relaxed** decision diagrams
  - Represent a superset of the feasible set
    - ... with a **limited-width** diagram.
  - The idea was first used to strengthen **propagation** in constraint programming solvers.
    - Andersen, Hadžić, JH, Tiedemann (2007)
    - Reduced 1 million node search trees to 1 node.

# Decision Diagrams

- Key idea: Use **relaxed** decision diagrams
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    - ... with a **limited-width** diagram.
  - The idea was first used to strengthen **propagation** in constraint programming solvers.
    - Andersen, Hadžić, JH, Tiedemann (2007)
    - Reduced 1 million node search trees to 1 node.
- Shortest (longest) path in the decision diagram provides a **bound** on optimal value.
  - Leads to general-purpose **optimization** method.

# Decision Diagrams



Exact diagram  
Width = 3

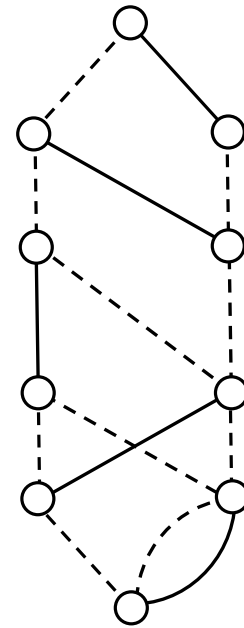
$x_1$

$x_2$

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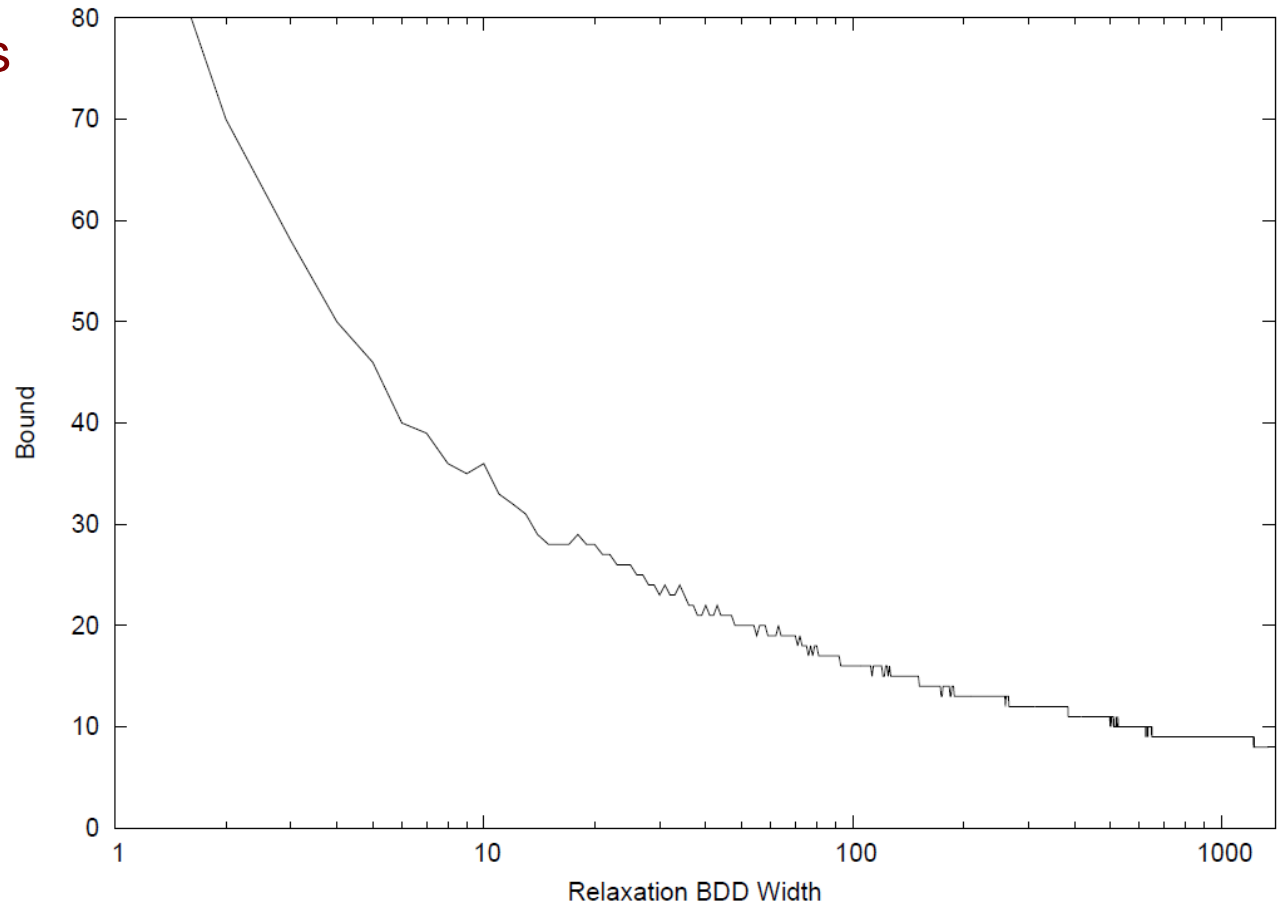
$x_5$



Relaxed diagram  
Width = 2

# Decision Diagrams

- Wider diagrams yield tighter bounds
  - But take longer to build.
  - Adjust width dynamically.



# Decision Diagrams

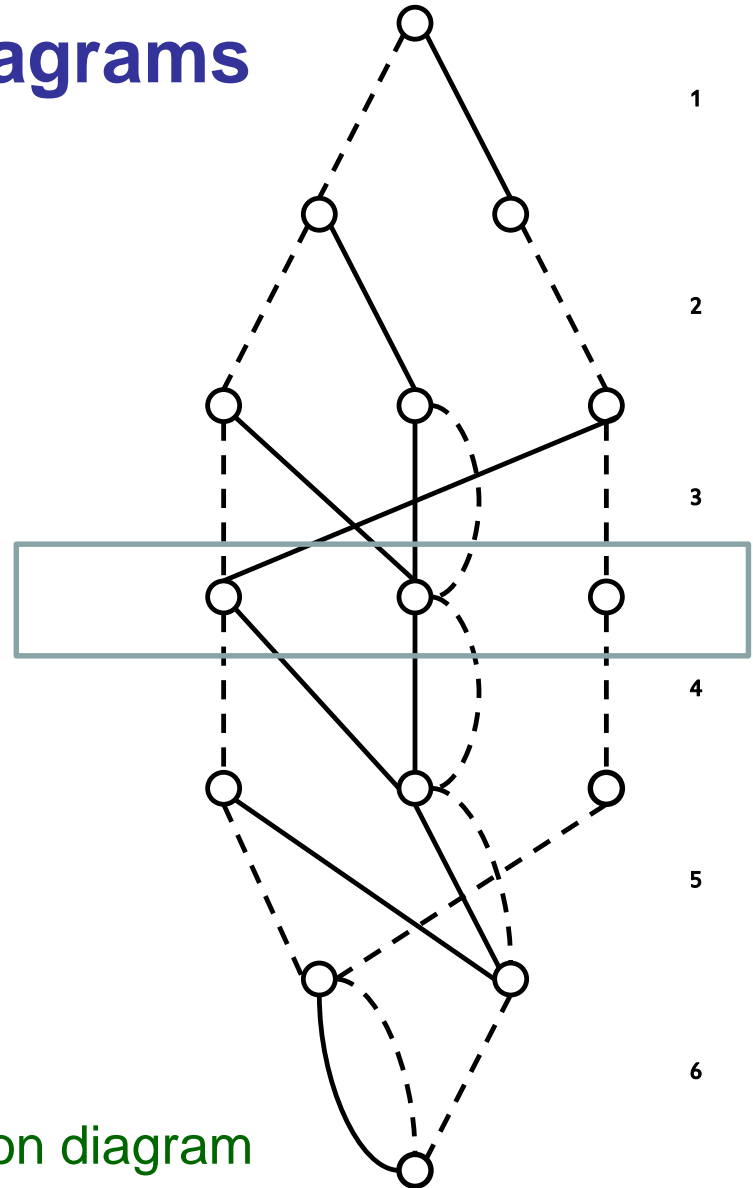
- Solve using a novel branch-and-bound algorithm.
  - Branch on nodes in **last exact layer** of relaxed decision diagram.
  - ...rather than branching on variables.



# Decision Diagrams

Branching in a relaxed decision diagram

Diagram is exact down to here

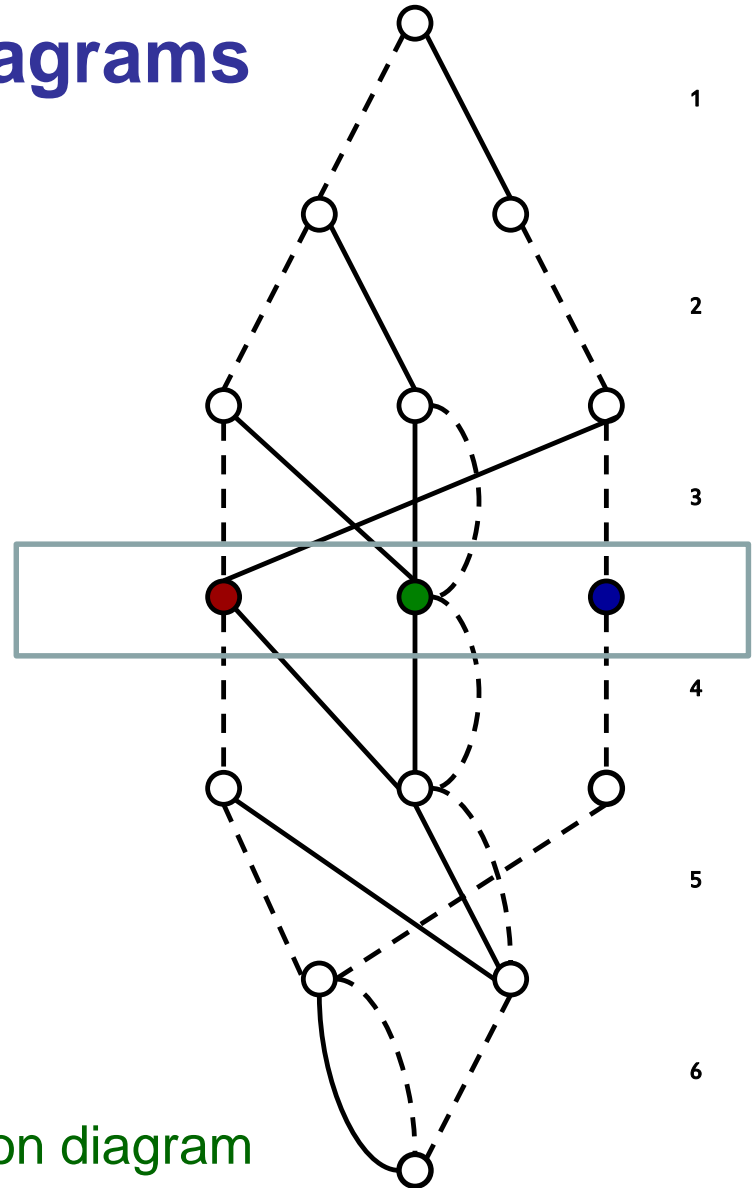


Relaxed decision diagram

# Decision Diagrams

Branching in a relaxed decision diagram

Branch on nodes in this layer



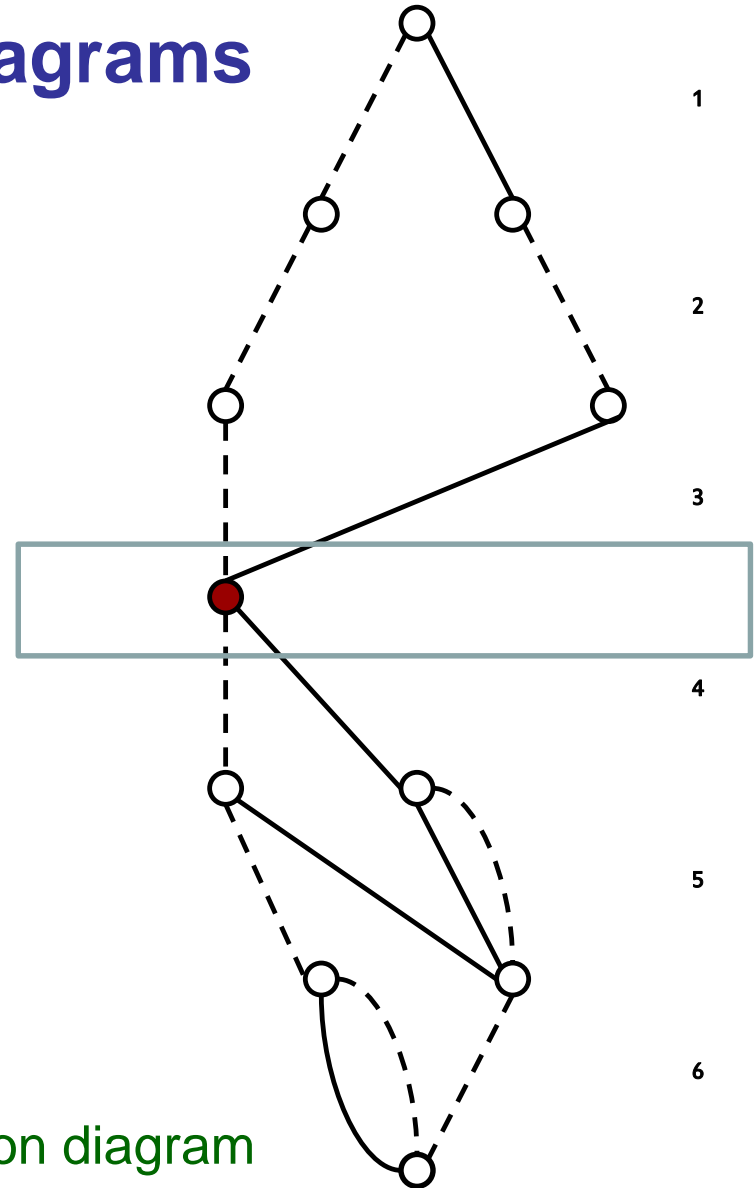
Relaxed decision diagram

# Decision Diagrams

Branching in a relaxed decision diagram

First branch

Relaxed decision diagram



1

2

3

4

5

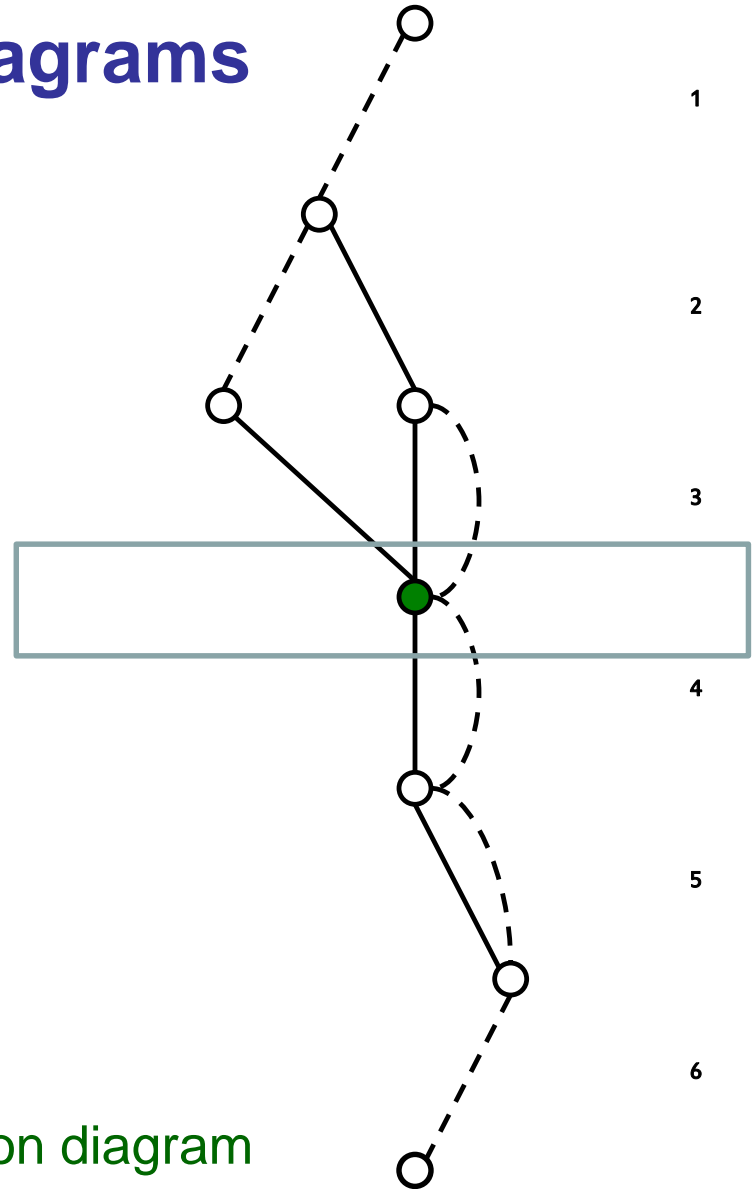
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# Decision Diagrams

Branching in a relaxed decision diagram

Second branch

Relaxed decision diagram



1

2

3

4

5

6

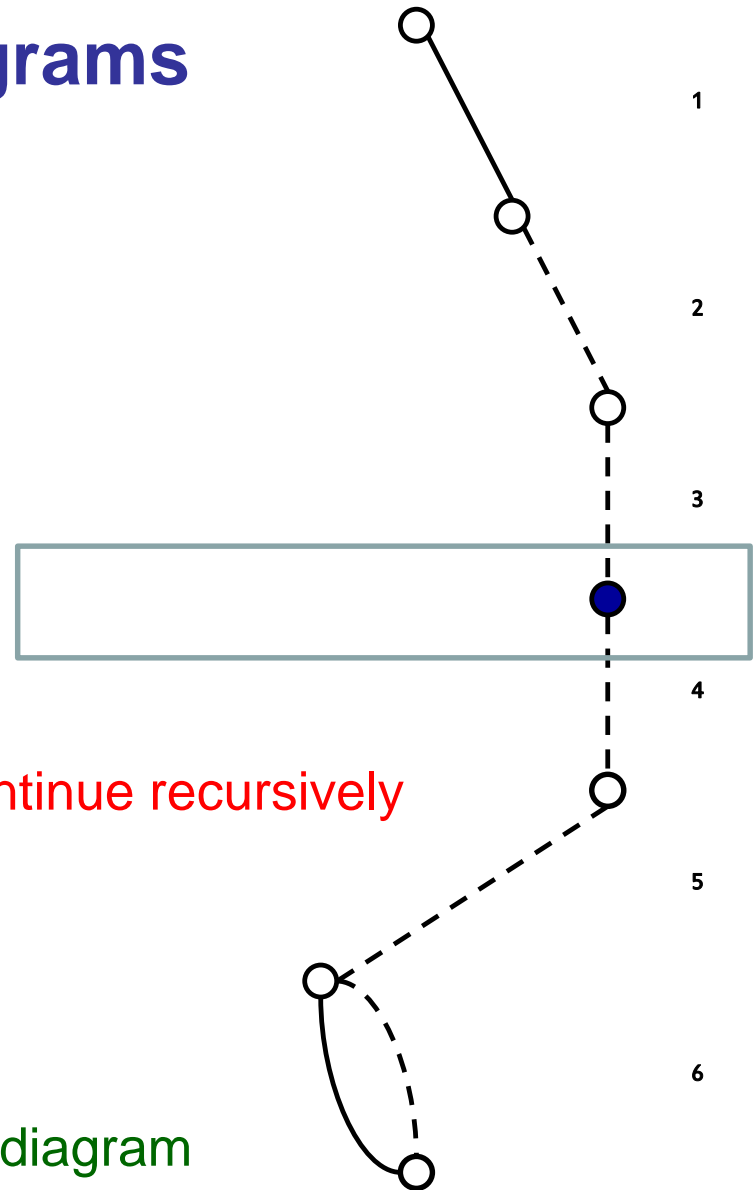
# Decision Diagrams

Branching in a relaxed decision diagram

Third branch

Continue recursively

Relaxed decision diagram



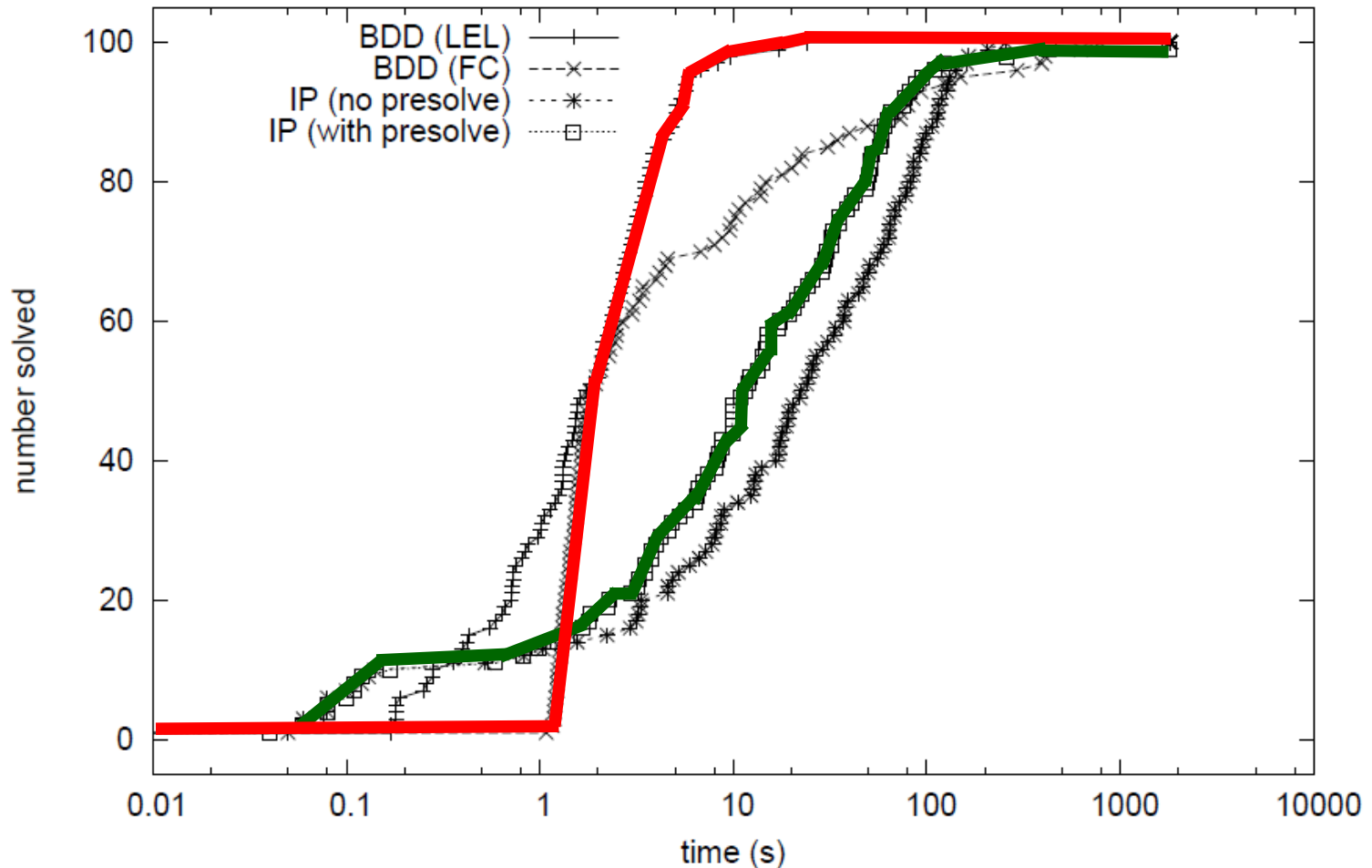
# Decision Diagrams

- Computational results...
  - Superior to state-of-the-art mixed integer solver on most instances tested.
    - Even when the problem has a natural MIP model.
    - Stable set, max cut, max 2-SAT.
    - Obtained best known solution on several max cut instances.

# Decision Diagrams

## Performance profile

Random  
max 2-SAT  
instances  
30 variables,  
100 instances



CPLEX 

Decision diagrams  23

# Decision Diagrams

- Potential to scale up
  - No need to load large inequality model into solver.
  - Parallelizes very effectively
    - Near-linear speedup.
    - Much better than mixed integer programming.



# Decision Diagrams

- Research direction:
  - Decision diagram technology is ready for **large-scale** applications from industry
    - ...which will also help develop the technology.

# Decision Diagrams

- Research direction:
  - Decision diagram technology is ready for **large-scale** applications from industry
    - ...which will also help develop the technology.
  - Give problems a **dynamic programming** model.
    - ...as required by decision diagrams.
    - But **don't** solve problems by dynamic programming.
    - Solve them using **branch and bound algorithm**.
  - New approach to the “curse of dimensionality.”
    - Solve DP models that were **previously intractable** due to exponential state space.

# Decision Diagrams

- Research direction:
  - Extend decision diagrams to **stochastic dynamic programming** and **optimal control**.
    - Introduce relaxed **stochastic** decision diagrams.
    - Develop an alternative to approximate dynamic programming.
  - Specialize to...
    - **partially observable state spaces**.
    - **adaptive control** (“data driven”)
  - Apply to large-scale problems.

# Decision Diagrams

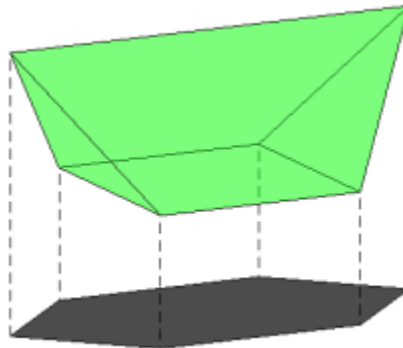
- Research direction:
  - Extend to **continuous global optimization**.
    - Use massive discretization of continuous variables.
  - Use **data driven optimization**.
    - Use sampling techniques as in “big data” analysis.
    - Develop alternatives to statistics and Lipschitz bounds for certainty guarantees.

# Decision Diagrams

- Research direction:
  - Perform in-depth **postoptimality analysis**.
    - Based on the fact that a decision diagram is a logic model.
    - **Deduce information** and **answer queries** about optimal and near-optimal solutions.
    - Can construct decision diagram based on optimal value obtained from another solver.

# Logic-Based Benders

- **Logic-based Benders decomposition** is a generalization of classical Benders decomposition.
  - Subproblem need not have linear or inequality model.
    - JH (1995), JH and Yan (1995), JH and Ottosson (2003).
- Solves a **projection** problem.
  - ...and therefore a **logical inference** problem.



# Logic-Based Benders

- Collaborators...
  - André Ciré
  - Elvin Çoban
  - Greger Ottosson
  - Erlendur Thorsteinsson\*
  - Hong Yan

\*2001 *Best Paper Award*, Constraint Programming conference

# Logic-Based Benders

- Fundamental concept: **inference duality**
  - **Optimization** and **logical inference** are two sides of the same coin.

Primal problem:  
optimization

$$\min f(x)$$

$$x \in \mathcal{S}$$

Find **best** feasible solution...  
by searching over **values of  $x$** .

Dual problem:  
Inference

$$\max v$$

$$x \in \mathcal{S} \stackrel{P}{\Rightarrow} f(x) \geq v$$

$$P \in \mathcal{P}$$

Find tightest bound that can  
be **inferred** from constraints...  
by searching over **proofs  $P$**

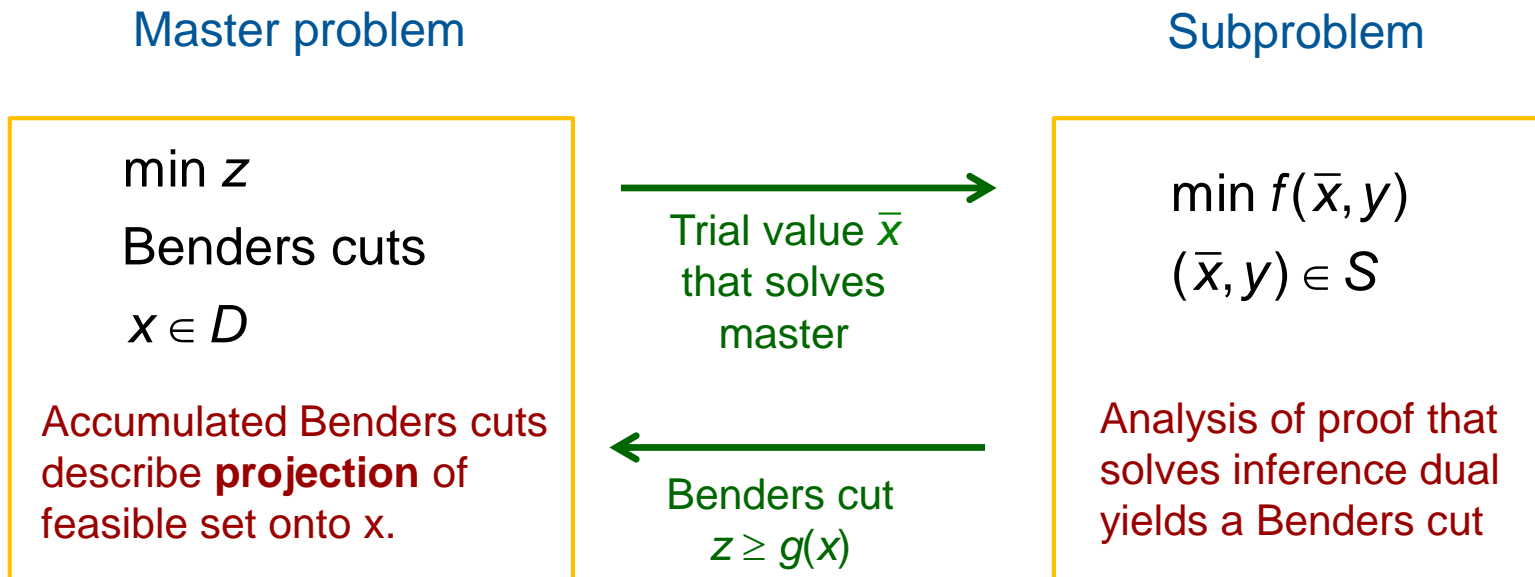


# Logic-Based Benders

- Popular optimization duals are special cases of the inference dual.
  - Result from different choices of inference method.
  - For example....
    - Linear programming dual
    - Lagrangean dual
    - Surrogate dual
    - Subadditive dual

# Logic-Based Benders

- Decompose problem into master and subproblem.
  - Subproblem is obtained by fixing some variables  $x$  to solution values in master problem.



# Logic-Based Benders

- Example: machine assignment and scheduling
  - Combines **mixed integer programming** and **constraint programming**

Master problem

Assign jobs to machines.

Solve problem by **mixed integer programming**.

Subproblem

Schedule jobs on each machine.

**Constraint programming** obtains proof of optimality (dual solution).

Use same proof to deduce cost for other assignments, yielding Benders cut.

→  
Trial  
assignment  
 $\bar{x}$

←  
Benders cut  
 $z \geq g(x)$

# Logic-Based Benders

- Substantial speedup for many applications.
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- Some applications:
  - Circuit verification
  - Chemical batch processing (BASF, etc.)
  - Steel production scheduling
  - Auto assembly line management (Peugeot-Citroën)
  - Automated guided vehicles in flexible manufacturing
  - Allocation and scheduling of multicore processors (IBM, Toshiba, Sony)
  - Facility location-allocation
  - Stochastic facility location and fleet management
  - Capacity and distance-constrained plant location

# Logic-Based Benders

- Some applications...
  - Transportation network design
  - Traffic diversion around blocked routes
  - Worker assignment in a queuing environment
  - Single- and multiple-machine allocation and scheduling
  - Permutation flow shop scheduling with time lags
  - Resource-constrained scheduling
  - Wireless local area network design
  - Service restoration in a network
  - Optimal control of dynamical systems
  - Sports scheduling

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    - By incorporating subproblem relaxation into master problem.
- Research direction (already begun)
  - Apply to data-driven **robust optimization**.
    - ...with uncertainty sets.
    - Uncertainty subproblem becomes Benders subproblem.
    - Now applying to IBM service center scheduling.



# Logic-Based Benders

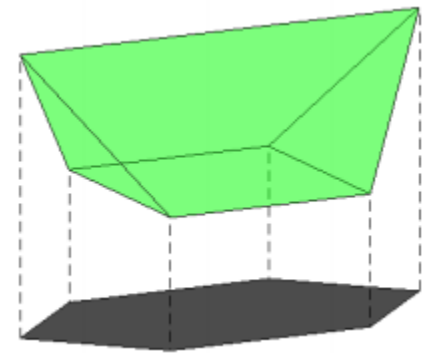
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  - Now applying to home health care scheduling, etc.
- Research direction
  - Apply to **logical inference** in large datasets...
    - Original application was to logic circuit verification.

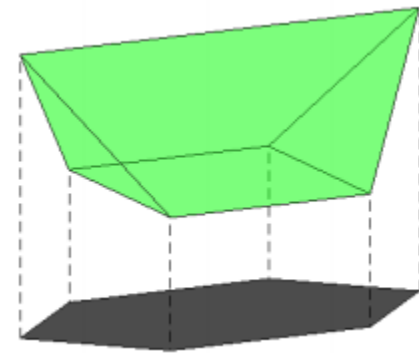
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  - Projection = extract information involving a subset of variables.
- Optimization...
  - **Project** feasible set onto a single variable representing the objective function.
- Inference...
  - **Project** knowledge base onto a subset of propositional variables.



# Logical Inference

- Example:
  - Knowledge base consists of logical clauses.
  - Derive all implications involving  $x_1, x_2$ .
  - This is a projection problem.

$$x_1 \vee x_2$$

$$\neg x_1 \vee x_3$$

$$\neg x_1 \vee \neg x_2 \vee \neg x_3$$

$$x_1 \vee x_3 \vee x_4$$

$$x_2 \vee x_3 \vee \neg x_4$$

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Projection



# Logical Inference

- Example:
  - Knowledge base consists of logical clauses.
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  - This is a projection problem.
- A classical projection method is resolution.
  - *Aside:* resolvents are a special case of Chvátal-Gomory cutting planes!
    - A basic optimization tool.

$$\begin{array}{l} x_1 \vee x_2 \\ \neg x_1 \vee x_3 \\ \neg x_1 \vee \neg x_2 \vee \neg x_3 \\ x_1 \vee x_3 \vee x_4 \\ x_2 \vee x_3 \vee \neg x_4 \end{array}$$

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Projection

# Logical Inference

- A central problem today:
  - Associate each inference with its **probability**, **relevance**, or **confidence**.
  - For example, IBM's **Watson** (Jeopardy player).



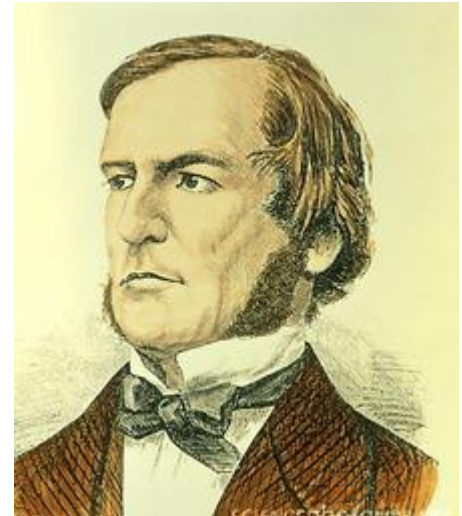
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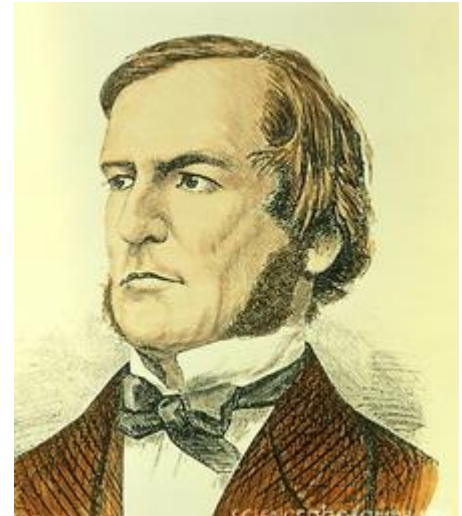
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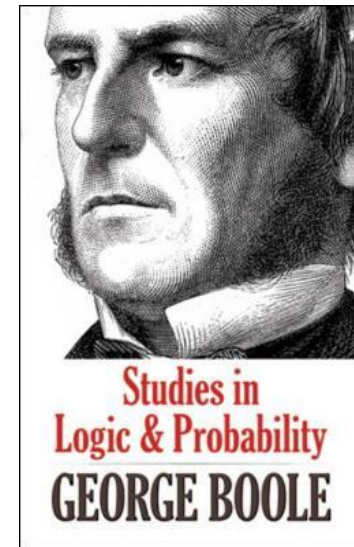
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- The problem was first posed for **probability**...
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    - He viewed **probability logic** as his most important contribution.
  - Boole also was the first to connect **optimization** with **logical inference**...



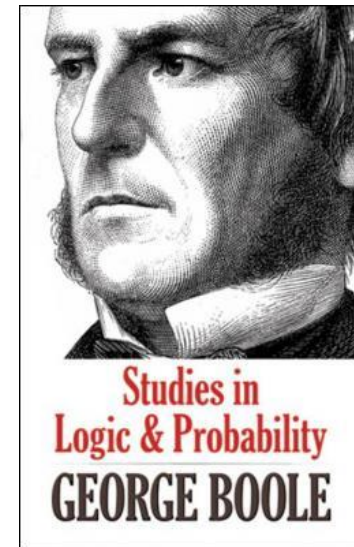
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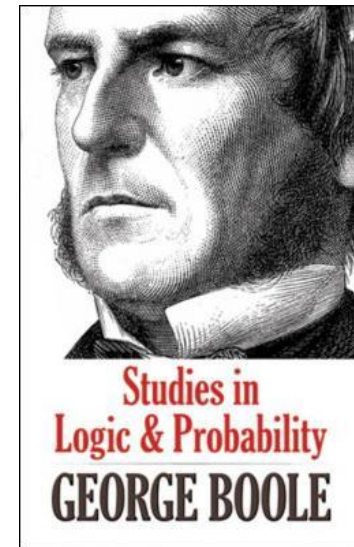
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    - We now call it **Fourier-Motzkin elimination**.
    - ...the best-known **projection** method for polyhedra!!
  - Boole not only connected optimization with logical inference, but connected both with **projection**.



# Logical Inference

- Research direction
  - Apply **large-scale optimization** methods to logical inference.
    - They are substantially **underutilized** for this purpose.
    - 1990s research in this area is newly relevant.
  - In particular:
    - Use **logic-based Benders** for propositional logic, etc.
    - Use **column generation** for probability logic.
    - Use **linear programming** for belief logics, relevance, and variations of Dempster-Shafer theory.
    - Use **decision diagrams** for queries and what-if analysis.