



Aalto-yliopisto
Perustieteiden
korkeakoulu

Extending the Decision Programming framework with continuous decisions (valmiin työn esittely)

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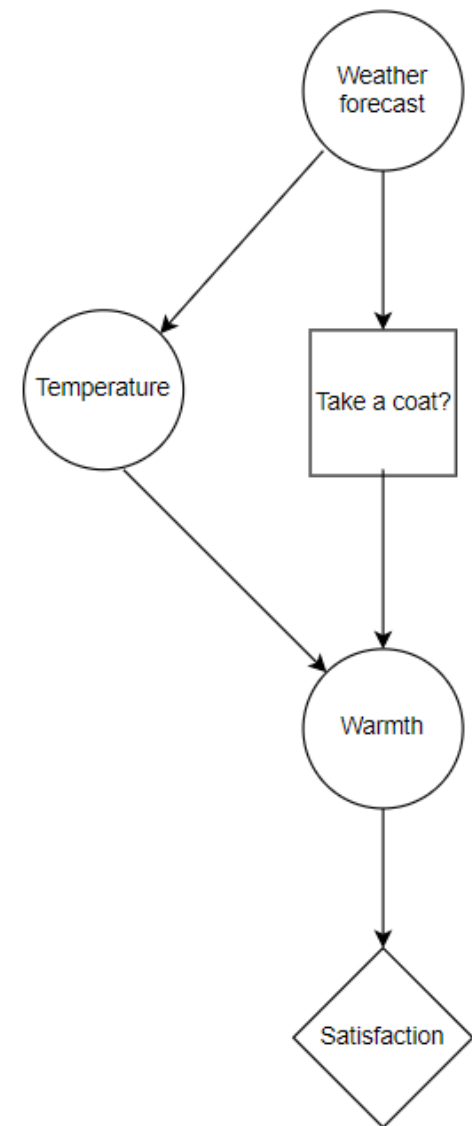
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Työn saa tallentaa ja julkistaa Aalto-yliopiston avoimilla verkkosivuilla. Muilta osin kaikki oikeudet pidätetään.

Influence diagram

- Acyclic directed graph
- Decision nodes (squares)
- Chance nodes (circles)
- Value nodes (diamonds)
- Arcs the flow of information
- Example diagram: choosing optimal clothing to match the weather



Decision Programming framework

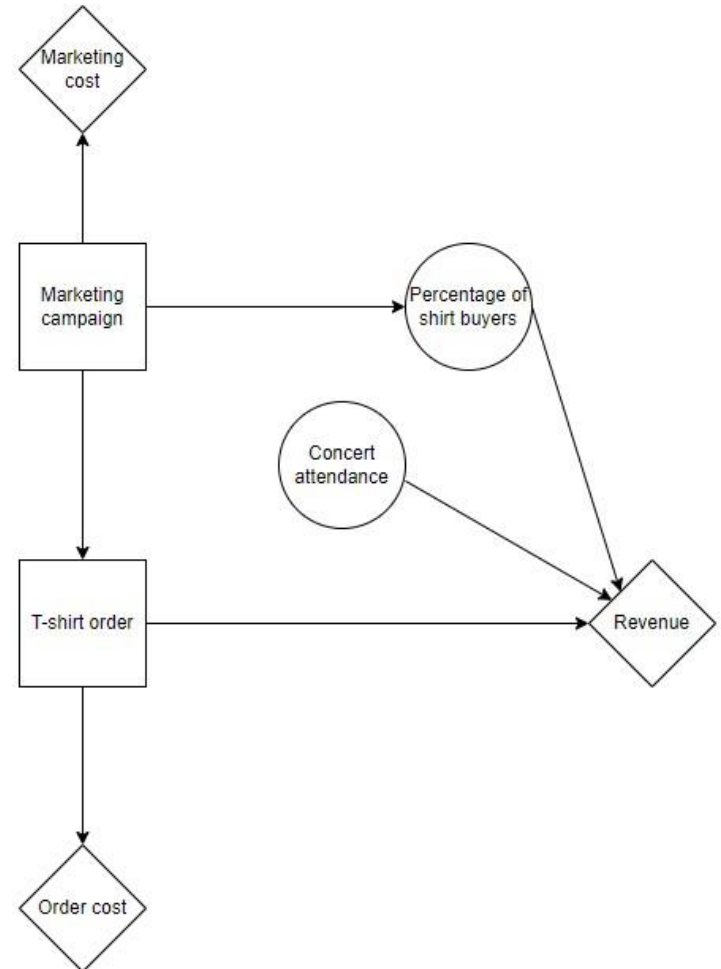
- Solving an influence diagram means finding the decision strategy that results in the best objective value
 - Often maximizing the expected utility
- The framework turns problems represented with influence diagrams into MILP problems
 - Solved with solvers like Gurobi
- Has a limitation that the decisions and chance events must have finite set of discrete states

Aim of the thesis

- Extend the Decision Programming framework to solve a simple problem having a continuous decision variable
- Solve a discrete and continuous version of the problem using Julia package DecisionProgramming.jl
- Compare the continuous and discrete formulations of the problem

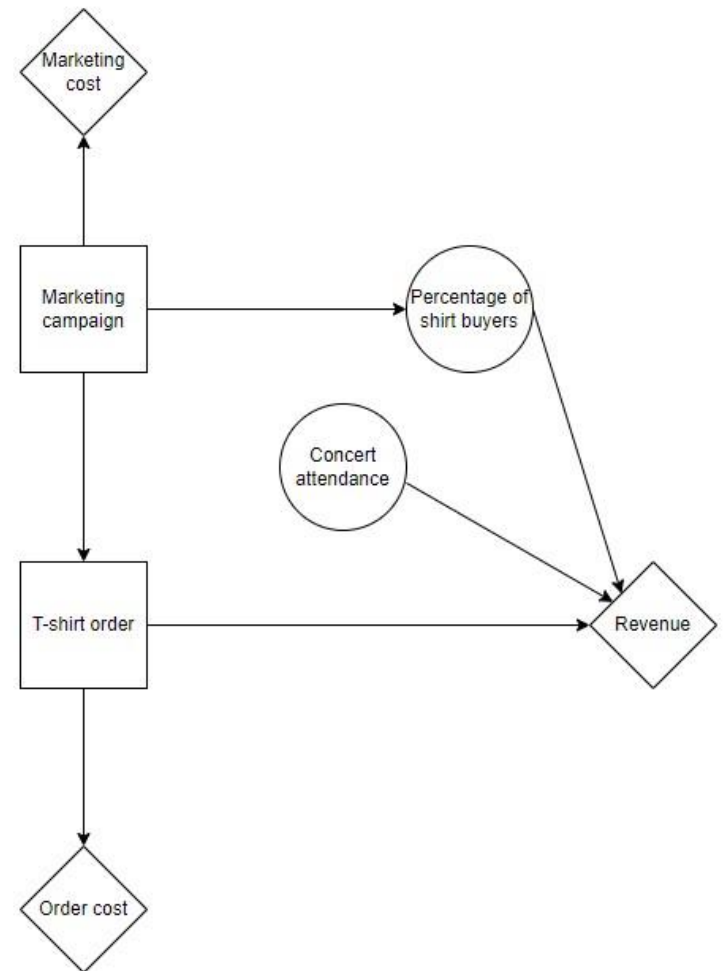
Example problem: T-shirt sales

- T-shirts sold in front of a concert venue
- Concert attendance and percentage of attendance who will buy the shirt are unknown
- T-shirt order size is modeled as a continuous decision
- A decision (yes/no) for arranging a marketing campaign
 - Increases the popularity of t-shirts among the attendees



Information states and paths

- An immediate predecessor of a node j is a node v that has an arc to the node j
- An information state $s_{I(j)}$ of a node j is the realizations of its immediate predecessor nodes
- A path s in a diagram is a sequence of realizations in the decision and chance nodes
 - (Yes, 5000_{shirts}, 70000_{attendees}, 10%)



The continuous extensions

- Continuous decision variables $y_{s_{I(i)}}$ are added, one for each set of paths that have a different realization for the information state $s_{I(i)}$ of the continuous decision i
- In our problem node i is the order size decision
 - i has two information states corresponding to the states of the marketing decision
- For each path \mathbf{s} , a function $U(\mathbf{s}, y_{s_{I(i)}})$ maps $y_{s_{I(i)}}$ and discrete chance and decision realizations to a utility value

Results

- In the discretized version the order size was broken into k discrete states
- With 5 or more states the discrete model was larger than the continuous on all measured scales
→ Continuous version is faster to solve

	Discrete version with k states	Continuous version
All variables	$20k + 2$	58
Binary variables	$2k + 2$	2
Constraints	$20k + 6$	98

Conclusions

- Continuous version has a smaller model size and gives an exact solution
 - Discrete version sufficient when approximations are enough
 - With a small problem it is also possible to use small number of states and iteratively update them to find optimum
- Similar reasoning could be applied to larger problems
- Restrictions:
 - The example is rather simple, and it gives not much insight on the computational performance on larger problems
 - The extended formulation is restricted to problems where there are no decision or chance nodes depending on the continuous decision

References

- Ahti Salo, Juho Andelmin, and Fabricio Oliveira. Decision programming for mixed-integer multi-stage optimization under uncertainty. *European Journal of Operational Research*, 299(2):550–565, 2022.
- Fabricio Oliveira, Olli Herrala, Jaan Tollander de Balsch, Helmi Hankimaa, ja Juho Andelmin. *DecisionProgramming.jl*, October 2021. URL <https://github.com/gamma-opt/DecisionProgramming.jl>
- Robert T Clemen and Terence Reilly. *Making hard decisions with DecisionTools*. Cengage Learning, 2013.