Outline

- Classification of Multi-Criteria Modelling Methods
- Aggregation and value functions
- Combining data mining and decision support
- Machine learning and revision of decision models
- Applications:
  - SMAC Advisor
  - Decision support in agriculture with GM crops
  - Data Mining: Workflows
  - Finance: Bank reputation risk

Multi-Criteria Methods

What is MCDA?

MCDA
Multi Criteria Decision Analysis
Multi Criteria Decision Aid(ing)

MCDM
Multi Criteria Decision Making
Multi Criteria Decision Modelling

MADA, MADM
Multi Attribute Decision ↑

Well-Known MCDM Methods

- AHP
- ANP
- DEA
- DEX
- DRSA
- ELECTRE
- GEA
- GMAA
- Kepner-Tregoe
- MACBETH
- MAUT
- MAVT
- ORCLASS
- PAPRIKA
- PROMETHEE
- ROR
- SAA
- SMART
- SWING
- TODIM
- TOPSIS
- UTA
- VDA
- VIKOR
- WPM
- WSM
- ZAPROS
- ... and many more...

MCMD Methods Classification

by Decision Task
("Problematic")
by Approach
("School")
by Information Type
Quantitative
by Acquisition
of Preferences
Direct
Indirect
Decision Support:
Advanced Topics
Jožef Stefan International Postgraduate School, Ljubljana
Course Web Page: http://kt.ijs.si/MarkoBohanec/DS/DS.html

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Jožef Stefan International Postgraduate School
Ljubljana, Slovenia

Marko Bohanec:
DS Advanced Topics
Decision Support 2018/19

Jožef Stefan International Postgraduate School
Ljubljana, Slovenia
Decision Tasks ("Problematics")

- Choosing and Ranking are equivalent (in theory)
- Sorting → Ranking
- Some methods are better than others for particular problematics

Kepner-Tregoe Method

AHP Method

Outranking Methods

Roy et al. (1965) - "The French School of MCDA"

General idea:
1. Take the set of alternatives \( X \)
2. And develop the outranking relation \( x \succeq y \) (\( x \) is at least as good as \( y \))
   (... in various ways, most often by pairwise comparison)

Consequence:
- Obtaining a partial or complete ranking of alternatives without developing an explicit evaluation/aggregation model

Important methods:
- ELECTRE
- PROMETHEE
**PROMETHEE Method**

Preference Ranking Organization METHOD for Enrichment Evaluation
Brans & Vincke (1985)

**Approach:**
Evaluation of differences between alternatives using preference functions
Aggregation by weighted flows

**Method characteristics:**
- Problematic: Choosing and Ranking
- Approach: Outranking
- Information: Quantitative
- Acquisition: Direct

**PROMETHEE Preference Functions**

Criterion I

\[ P_k(a, b) = \frac{v(a) - v(b)}{v(a) - v(b)} \]

Criterion II

\[ P_k(a, b) = \frac{v(a) - v(b)}{v(a) - v(b)} \]

Criterion III

\[ P_k(a, b) = \frac{v(a) - v(b)}{v(a) - v(b)} \]

Criterion IV

\[ P_k(a, b) = \frac{v(a) - v(b)}{v(a) - v(b)} \]

Criterion V

\[ P_k(a, b) = \frac{v(a) - v(b)}{v(a) - v(b)} \]

Criterion VI

\[ P_k(a, b) = \frac{v(a) - v(b)}{v(a) - v(b)} \]

**PROMETHEE Evaluation**

Preference degree:
\[ \pi(a, b) = P_k[v(a) - v(b)] \]

Multicriteria preference degree:
\[ \pi(a, b) = \sum_{k=1}^{n} w_k P_k(a, b) \]

Preference flows:
positive \[ \phi^+(a) = \frac{1}{n-1} \sum_{x \epsilon A} \pi(x, a) \]

negative \[ \phi^-(a) = -\phi^+(a) \]

Net flow:
\[ \phi(a) = \phi^+(a) - \phi^-(a) \]

**TOPSIS Method**
TOPSIS Method

Technique for Order of Preference by Similarity to Ideal Solution

Heang & Yoon (1981)

Idea:
The chosen alternative should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution

Method characteristics:
- Problematic: Choosing and Ranking
- Approach: Reference (ideal solutions)
- Information: Quantitative
- Acquisition: Direct

TOPSIS Example (1/3)

Decision matrix (using any units)

<table>
<thead>
<tr>
<th>Weight</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>10%</td>
<td>4</td>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>Salary</td>
<td>50%</td>
<td>500</td>
<td>4500</td>
<td>3000</td>
</tr>
<tr>
<td>MS</td>
<td>25%</td>
<td>4</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Long</td>
<td>15%</td>
<td>10</td>
<td>1</td>
<td>6</td>
</tr>
</tbody>
</table>

Normalised matrix

$\mathbf{r}_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}}$

<table>
<thead>
<tr>
<th>Weight</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>0.346</td>
<td>0.518</td>
<td>0.777</td>
<td>0.086</td>
</tr>
<tr>
<td>Salary</td>
<td>0.086</td>
<td>0.777</td>
<td>0.518</td>
<td>0.346</td>
</tr>
<tr>
<td>MS</td>
<td>0.396</td>
<td>0.099</td>
<td>0.693</td>
<td>0.594</td>
</tr>
<tr>
<td>Long</td>
<td>0.808</td>
<td>0.081</td>
<td>0.485</td>
<td>0.323</td>
</tr>
</tbody>
</table>

TOPSIS Example (2/3)

Normalised matrix

<table>
<thead>
<tr>
<th>Weight</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>0.346</td>
<td>0.518</td>
<td>0.777</td>
<td>0.086</td>
</tr>
<tr>
<td>Salary</td>
<td>0.086</td>
<td>0.777</td>
<td>0.518</td>
<td>0.346</td>
</tr>
<tr>
<td>MS</td>
<td>0.396</td>
<td>0.099</td>
<td>0.693</td>
<td>0.594</td>
</tr>
<tr>
<td>Long</td>
<td>0.808</td>
<td>0.081</td>
<td>0.485</td>
<td>0.323</td>
</tr>
</tbody>
</table>

Weighted normalised matrix

$\mathbf{v}_{ij} = w_j r_{ij}$

<table>
<thead>
<tr>
<th>Weight</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>0.035</td>
<td>0.052</td>
<td>0.078</td>
<td>0.009</td>
</tr>
<tr>
<td>Salary</td>
<td>0.043</td>
<td>0.389</td>
<td>0.259</td>
<td>0.173</td>
</tr>
<tr>
<td>MS</td>
<td>0.099</td>
<td>0.025</td>
<td>0.173</td>
<td>0.149</td>
</tr>
<tr>
<td>Long</td>
<td>0.121</td>
<td>0.012</td>
<td>0.073</td>
<td>0.049</td>
</tr>
</tbody>
</table>

TOPSIS Example (3/3)

Calculate Euclidean distances from ideal and negative ideal alternatives

<table>
<thead>
<tr>
<th>Distance from Min</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>0.135</td>
<td>0.348</td>
<td>0.278</td>
<td>0.183</td>
</tr>
<tr>
<td>Salary</td>
<td>0.356</td>
<td>0.186</td>
<td>0.138</td>
<td>0.239</td>
</tr>
</tbody>
</table>

Evaluate

$V_j = \frac{1}{\sum_{i=1}^{n} \frac{D_{ij}^{min}}{D_{ij}^{max} - D_{ij}^{min}}}$

Disaggregation/Aggregation Approach

by Decision Task
- "Problematic"
- "School"

MCDM Methods Classification

by Information Type
- Quantitative
- Qualitative

by Acquisition of Preferences
- Indirect
- Direct

by Approach
- General idea:
  1. Take some alternatives with known evaluations
  2. Develop a general evaluation/aggregation procedure

In other words:
- Similar to regression/approximation methods
- "Machine Learning of MCDM"

Important methods:
- UTA (+UTADIS, UTA GMS, GRIP, ...)
- ROR (Robust Ordinal Regression)
**UTA Method**

UTilites Additive
Jacquet-Lagrèze & Siskos (1982)

Idea:
- Given a set of alternatives \( X = \{ x_1, x_2, \ldots, x_n \} \), \( j = 1, 2, \ldots, n \),
- develop piecewise linear marginal utility functions \( u_j(x_j) \),
- so that \( u_j(x_j) = \sum_{i=1}^{n} w_i u_i(x_i) \) optimally approximates \( X \).

Method:
Optimization by a linear program

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**UTA Example** (application on a DEX model)

**Aggregation and Value Functions**

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**Quantitative Multi-Attribute Model for Car Selection**

**Qualitative Multi-Attribute Model for Car Selection**
Aggregation Functions in Math

Aggregation function:

\[ \text{Agg} : [0,1]^n \rightarrow [0,1] \]

\[ y = \text{Agg}(x_1, x_2, ..., x_n) \]

Conditions:

1. Identity when unary:
   \[ \text{Agg}(x) = x \]

2. Boundary conditions:
   \[ \text{Agg}(0,0, ..., 0) = 0 \]
   \[ \text{Agg}(1,1, ..., 1) = 1 \]

3. Non-decreasing:
   \[ (x_1, x_2, ..., x_n) \leq (y_1, y_2, ..., y_n) \Rightarrow \text{Agg}(x_1, x_2, ..., x_n) \leq \text{Agg}(y_1, y_2, ..., y_n) \]

Value Functions

Quantitative Multi-Attribute Model for Car Selection

Value Function

<table>
<thead>
<tr>
<th>OPTION</th>
<th>CAR</th>
<th>PRICE</th>
<th>FUEL</th>
<th>SAFETY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Options</td>
<td>1</td>
<td>50 x P_1 + 20 x P_2 + 30 x P_3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Value of Options

1. 22,000 8 6 63
2. 26,000 6 9 72
3. 19,000 7 8 88

Single Attribute: Marginal Value Function

Modelling of Preferences

Linear Aggregation Functions

\[ y = \sum_{i=1}^{n} w_i x_i \]

Minimum and Maximum

\[ y = \min(x_1, x_2) \]

\[ y = \max(x_1, x_2) \]
Multiplicative Aggregation Functions

\[ y = y(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} x_i \]

\[ y = x^2 \]

Continuous Logic Functions

\[ y = y(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} w_i x_i \]

Linear Aggregation of Partial Value Functions

\[ y = y(p_1(x_1), p_2(x_2), \ldots, p_n(x_n)) \]

Qualitative Multi-Attribute Model for Car Selection

Utility Function Defined By Elementary Decision Rules

<table>
<thead>
<tr>
<th>SAFETY</th>
<th>PRICE</th>
<th>CAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>bad</td>
<td>high</td>
<td>unacceptable</td>
</tr>
<tr>
<td>bad</td>
<td>medium</td>
<td>unacceptable</td>
</tr>
<tr>
<td>bad</td>
<td>low</td>
<td>unacceptable</td>
</tr>
<tr>
<td>acceptable</td>
<td>high</td>
<td>unacceptable</td>
</tr>
<tr>
<td>acceptable</td>
<td>medium</td>
<td>acceptable</td>
</tr>
<tr>
<td>acceptable</td>
<td>low</td>
<td>acceptable</td>
</tr>
<tr>
<td>good</td>
<td>high</td>
<td>unacceptable</td>
</tr>
<tr>
<td>good</td>
<td>medium</td>
<td>acceptable</td>
</tr>
<tr>
<td>good</td>
<td>low</td>
<td>good</td>
</tr>
<tr>
<td>excellent</td>
<td>high</td>
<td>unacceptable</td>
</tr>
<tr>
<td>excellent</td>
<td>medium</td>
<td>good</td>
</tr>
<tr>
<td>excellent</td>
<td>low</td>
<td>excellent</td>
</tr>
</tbody>
</table>

Value Function Defined Point-By-Point
Utility Function Defined Point-By-Point - Linearised

Value Function Defined Point-By-Point - Interpolated

Non-Linear Aggregation of Attributes

Combining Data Mining and Decision Support

Example: Cars
**DM + DS Integration?**

Data Mining | Decision Support

DM + DS Integration!

"Decision Support for Data Mining" | "Data Mining for Decision Support"
Integrating DM and DS through Models

**DM + DS Integration: Academic**

DM: Weka | Data | DM: HINT

**Parallel Applications: Multiple DM models, then DS**

Data Mining | Model 1 | Decision Support | Model 2 | Model 3

**Problem: Prediction of Academic Achievement**

Primary School | High School

1 | 1 | 5: graduates: 4 or 5
2 | 2 | 4: graduates: 2 or 3
3 | 3 | 3: prolonged
4 | 4 | 2: fails soon
5 | 5: | 1: fails late

**Literature**

DATA MINING AND DECISION SUPPORT Integration and Collaboration

**DEXi 14.8.02**

Drevo kriterijev
Kriterij Opis
final achievement
c5
c1
for lang 8th grade
gen ach 7th grade
c2
regular enrol
for lang
c7
c3
citizenship
birth state
c6
gen ach prim sch
c4
math 8th grade
phys 8th grade
Marko Bohanec: DS Advanced Topics

Applications

SMAC Advisor
Decision Problem

Problem:
Can GM maize be grown in coexistence with plants on other fields?

Criterion:
Genetic interference (Adventitious Presence)
Typical target AP: 0.9 %

Factors:
pollen flow, volunteers, feral plants, mixing during harvesting, transport, storage and processing, human error, accidents, ...

SMAC Advisor
Decision support software that assesses the achievable AP given:
- relation between fields: distance, relative size, wind direction, etc.
- type and characteristics of used seeds
- environmental characteristics (e.g., background GM pollen pressure)
- use of machinery (e.g., sharing with other farmers)
- target AP

... and gives recommendations:
- farming allowed
- farming disallowed
- assess risks (coexistence is possibly achievable)
- assess additional measures (coexistence achievable by small changes)

SMAC Advisor Architecture

SMAC Advisor Wizard
User Interface
Co-Existence
Multi-Attribute DEXi Model
MAPOD
Simulation Results

SMAC Advisor Level 3: MAPOD® Simulator

Advanced simulator that assesses the rate of cross-pollination

Some MAPOD® Results

New case studies on the coexistence of GM and non-GM crops in European agriculture
EUR 22102 EN
SMAC Advisor Level 2: DEXi Model

Qualitative Multi-Attribute Model

SMAC Advisor Level 2: Formulation of Rules

SMAC Advisor Level 1: User Interface

SMAC Advisor Level 1: User Interface

EU Projects on GM organisms

ECOGEN 2003-2006 http://www.ecogen.dk/
Soil ecological and economic evaluation of genetically modified crops

Sustainable introduction of genetically modified crops into European agriculture

Co-existence and traceability of GM and non-GM supply chains
**Machine Learning and DEX Models**

**HINT:** Learning DEXi Models From Data

**Introduction**
- Multi-Attribute Decision Making: decompose the problem to less complex subproblems
- **DEX:** An Expert System Shell for MADM
  - qualitative attributes
  - decision rules

**Problem**
Development of hierarchical decision models is difficult

Given decision examples taken from
- existing database of past decisions or
- provided explicitly by decision-maker,
**develop a corresponding model (hierarchy + functions)**

**Example**
- What is the result of “traditional” decision-tree learning, such as See5?
- How does this table look in DEX?
- How to create a hierarchical DEXi model from this table?
**Decision Tree (See5)**

- What is the result of "traditional" decision-tree learning, such as See5?
- How does this table look in DEXi?
- How to create a hierarchical DEXi model from this table?

**Boolean Function Decomposition**

```
x 1 x 2 x 3 y
lo lo lo lo
lo med lo lo
lo med hi med
lo hi lo lo
lo hi hi hi
med med lo med
med hi hi hi
hi lo lo hi
hi hi lo hi
```

**Decomposition method HINT**

Extended Ashenhurst-Curtis decomposition of Boolean functions:
- adapted to development of multi-attribute decision models
- multi-valued attributes
- unsupervised and supervised decomposition
- partition selection measures
- generalization

Restriction:
- nominal attributes and utility

Candidate decompositions

\[
\begin{align*}
\text{candidate } & x_1 | x_2, x_3 \\
\text{candidate } & x_2 | x_1, x_3 \\
\text{candidate } & x_3 | x_1, x_2
\end{align*}
\]