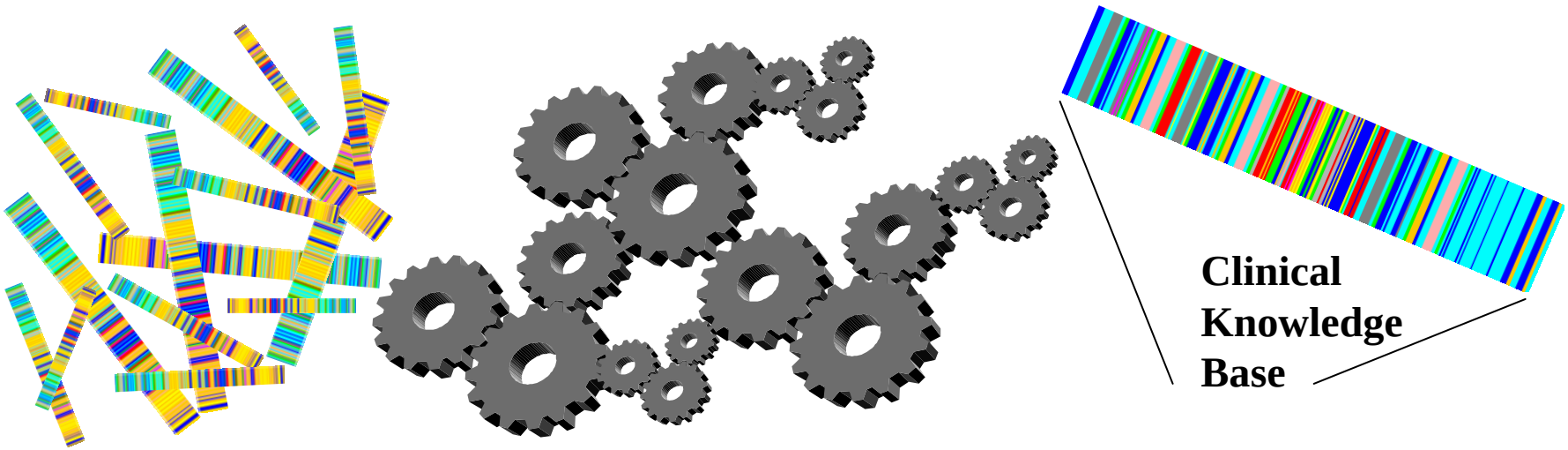
Explaining Clinical Decisions by Extracting Regularity Patterns



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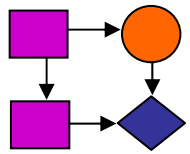
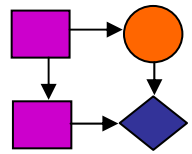


Introduction

•When solving clinical decision-making problems with modern graphical decision-theoretic models such as influence diagrams, we obtain decision tables with optimal decision alternatives describing the best course of action for a given patient or group of patients

•For real-life clinical problems, these tables are often extremely large and this is an obstacle to understanding their content

•We propose *KBM2L* lists are structures that minimize memory storage requirements for these tables, and, at the same time, improve their knowledge organization

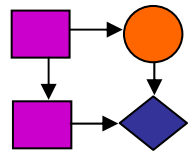


Introduction

•The resulting improved knowledge organization can be interpreted as explanations of the decision-table content

•We explore the use of *KBM2L* lists in analyzing and explaining optimal treatment selection in patients with non-Hodgkin lymphoma of the stomach using an expert-designed influence diagram as an experimental vehicle

•The selection of the appropriate treatment for non-Hodgkin lymphoma of the stomach is, as for many other types of cancer, difficult, mainly because of the uncertainties involved in the decision-making process



Introduction

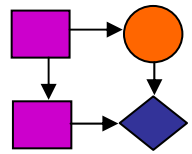
•We look at an expert-designed clinical influence diagram as a representation of a body of clinical knowledge

•This diagram can be analyzed and explained using *KBM2L* lists

•It is shown that the resulting lists provide high-level explanations of optimal treatments for the disease

•These explanations are useful for finding relationships between groups of variables and treatments

•It is demonstrated that these lists can act as a basis for gaining a deeper understanding of the underlying clinical problem



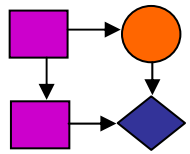
Introduction

This talk proposes a method to produce explanations for the optimal policies of decision-making problems solved by means of Influence Diagrams

The main reasons are:

•the exponential size of the decision tables and the need of knowledge synthesis

•the need of useful explanations for the expert users and support for the validation process



Introduction

Our approach is similar to other techniques like:

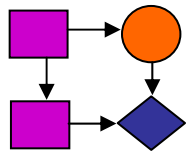
- tree-based classifiers
- oblivious read-once decision graphs
- rough sets

But the decision tables have not uncertainty and all cases are correctly classified by the inferred model

We rebuild the decision tables as a list and search the best configuration:

- minimum storage space and
- maximum explanation performance

A realistic clinical model allows us to show how our method extracts patterns from the decision tables and sets the explanations.
Gastric NHL model: non-Hodgkin lymphoma of the stomach.

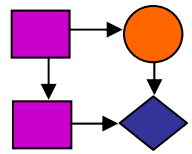


Introduction

•**DECISION SUPPORT SYSTEMS**
- A system (software) that supports the decision process
- Domain knowledge representation, problem specification, evaluation of solutions, explanation and sensitivity analysis

•**INFLUENCE DIAGRAM (ID)**
- Probabilistic graphical model of a decision problem
- Decision strategy tables (**DST**)

•**EXPLANATION (EX)**
- Why the DSS shows a particular feature set?
-What the implicit rules underlying the modelled decision problem are?



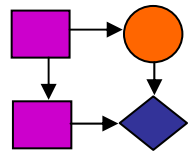
Introduction

Decision Problem → ID (Model)

Evaluation → DST (Knowledge)

KBM2L → Knowledge Base

User Interface → **Decision Support System**

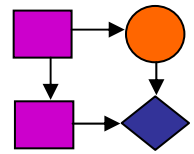


Introduction

DST → **KBM2L**

- Knowledge Base

Representation	→	Multidimensional Matrix to List
Synthesis	→	**ITEM granularity**
Explanation	→	Relevant Attribute Subset
Validation	→	Expert Reasoning Rules



Using KBM2L
lists for explanation purposes

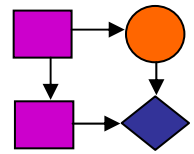
Basic concepts:

Fernandez del Pozo, J.A., Bielza, C., Gomez, M.:
A List-Based Compact Representation for
Large Decision Tables Management.
European Journal of Operational Research, volumen 160,
Special Issue on Decision Making and AI, (2005) 638-662

KBM2L ---
Knowledge Base Matrix to List

•Every DST is arranged in a multidimensional matrix and consecutive cells with the same optimal alternative are grouped

•We search the lists with fewer groups (ITEMS) regarding the index of the cells, when a particular order (BASE) in the variable set, and the values of their discrete domains are choosen



Using KBM2L
lists for explanation purposes

Basic concepts:
KBM2L --- Knowledge Base Matrix to List

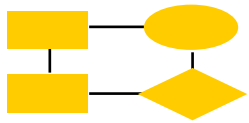
Optimal BASE → Minimum ITEM length.
Optimal BASE ← Heuristic Search + GA +VNA

Explanations using relevant variables

•Each ITEM has two extreme cases (I_{inf}, I_{Sup}) that explain its optimal alternative: $I_{inf} \wedge I_{Sup}$

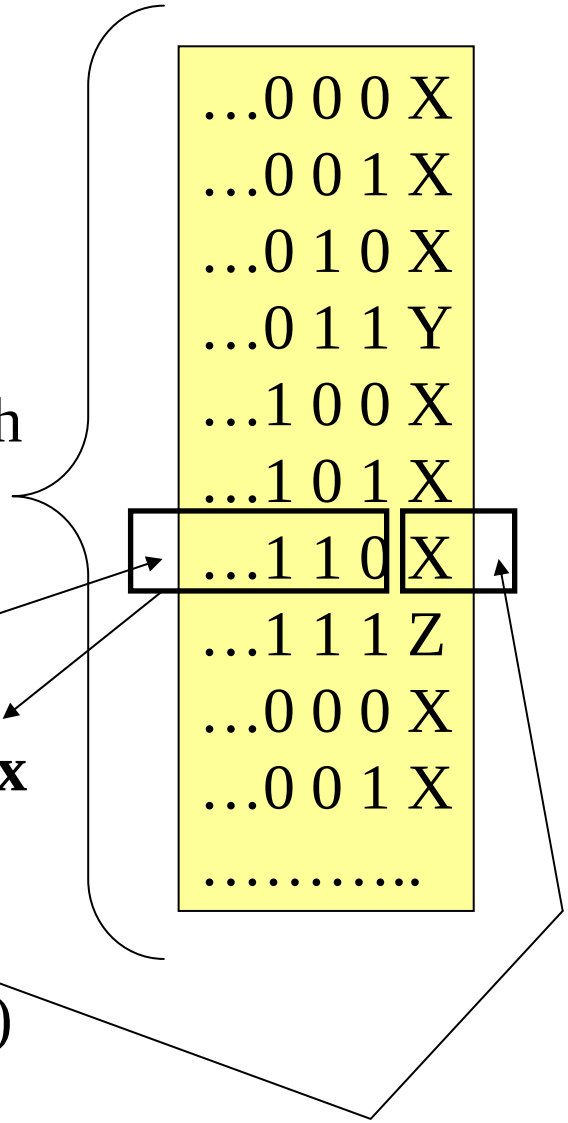
•The BASE classifies the variables as relevant if their values are the same in both extreme cases

KBM2L



•The ID evaluation yields a DST defined by its attributes (and their domains) with all configurations: A0 A1 A2

•Each strategy consists of:
an attribute configuration
an optimal alternative



•We can arrange the list of strategies according to any order on the attribute set (base)

•All adjacent strategies are grouped if they have the same optimal alternative; one configuration represents the group

KBM2L

•An order change (base permutation) may induce a specific knowledge granularity **<(...),...|**

[A0,A1,A2]
[A1,A0,A2]
[A2,A1,A0]
…….
[A0,A2,A1]

DST {A0,A1,A2}

0	0 0 X
0	0 1 X
0	1 0 Y
0	1 1 X
1	0 0 X
1	0 1 Z
1	1 0 X
1	1 1 X

[A0,A1,A2]

< (001), X|
< (010), Y|
< (100), X|
< (101), Z|
< (111), X|

[A1,A0,A2]

< (010), X|
< (011), Z|
< (100), Y|
< (111), X|

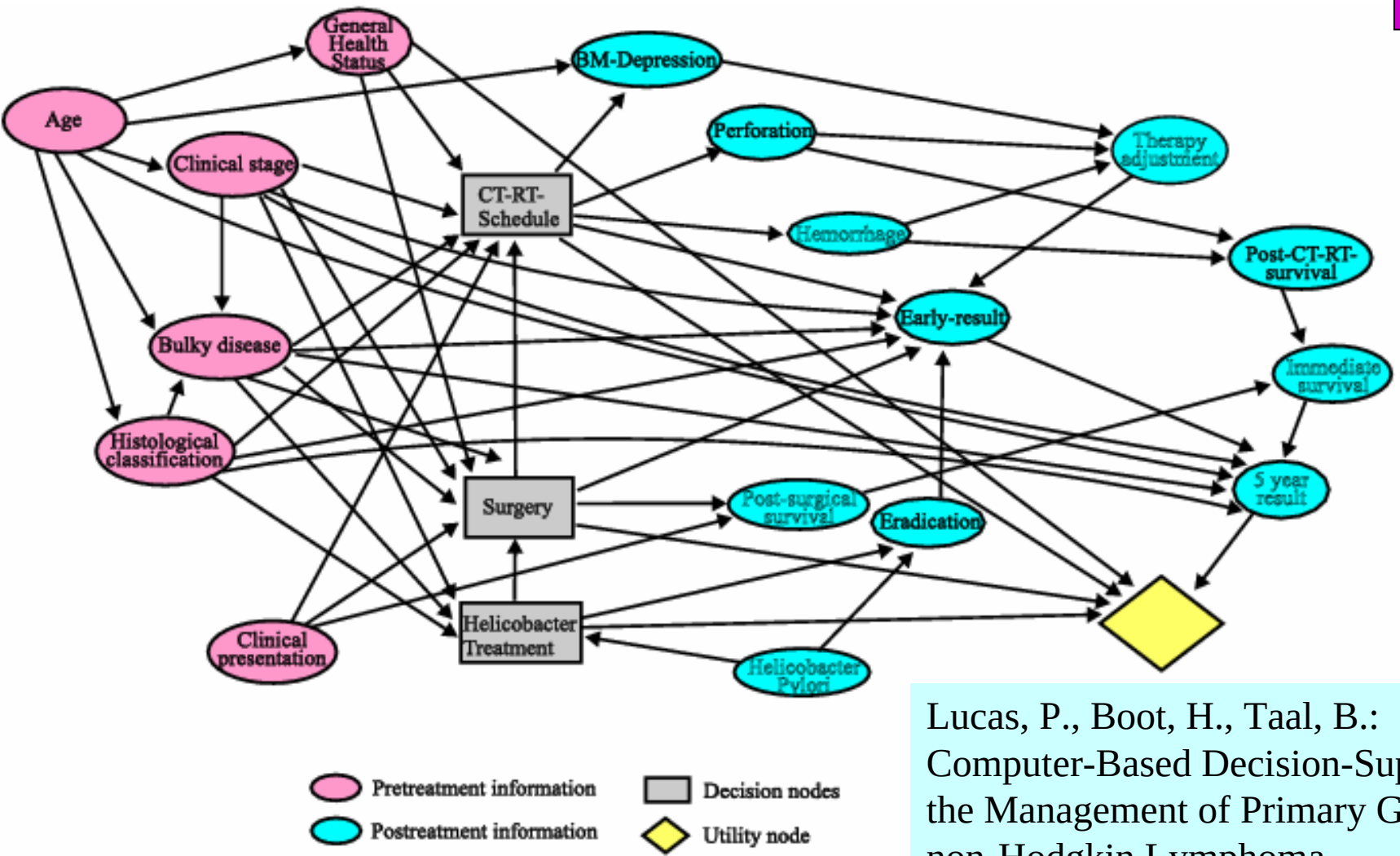
•The most compact KBM2L allows to extract general and concise explanations

X → (00_) ∨ (010)
X → (11_) ∨ (101)

Explanation is the set of constant values in the index

X → (00_) X → (011) ∨ (100) X → (11_)

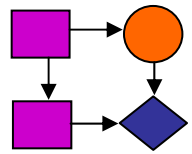
The Gastric non-Hodgkin Lymphoma Diagram



Lucas, P., Boot, H., Taal, B.: Computer-Based Decision-Support in the Management of Primary Gastric non-Hodgkin Lymphoma. Methods of Information in Medicine, 37 (1998) 206-2

Chronic infection Helicobacter pylori.
5% of gastric tumors. The model can make a diagnosis and suggest a treatment.

The Gastric non-Hodgkin Lymphoma Diagram



The influence diagram

•17 chance nodes (ellipses), 1 value node (diamond) and 3 decision nodes (rectangles).

•42 arcs, 8,282 probability entries and 144 utility entries.

The evaluation results: attributes and values

helicobacter-treatment (HT)	*No, Yes*
surgery (S)	*None, Curative, Palliative*
ct-rt-schedule (CTRTS)	*None, Radio, Chemo, Ch.Next.Rad*
general-health-status (GHS)	Poor, Average, Good
clinical-stage (CS)	I, II1, II2, III, IV
bulky-disease (BD)	Yes, No
histological-classification (HC)	Low.Grade, High.Grade
helicobacter-pylori (HP)	Absent, Present
clinical-presentation (CP)	None, Hemorrhage, Perforation, Obstruction

Results: Optimal Decision Tables and KBM2L List

HT: [CS,BD,HC,HP], 40 cases, 17 items

32 cases – HT=No, 8 cases – HT=Yes

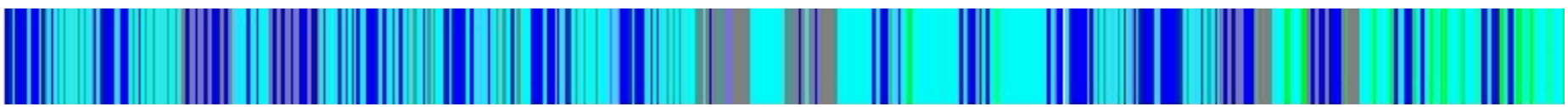
S: [GHS,HT,CS,BD,HC,HP,CP], 960 cases, 385 items

663 cases – S=None, 297 cases – S=Curative

CTRTS: [GHS,S,HT,CS,BD,HC,HP,CP], 2880 cases, 678 items

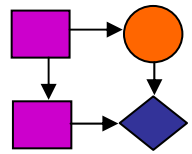
490 cases – CTRTS=None, 668 cases – CTRTS=Radio,

1404 cases – CTRTS=Chemo, 124 cases – CTRS=Ch.Next.Rad



Evaluation of the ID yielded 3 decision tables each containing the optimal treatment for each combination of attributes.

Example of table HT: ODT and KBM2L, Opt-KBM2L



0 0 0 0	0	2 1 0 0	0
0 0 0 1	1	2 1 0 1	1
0 0 1 0	0	2 1 1 0	0
0 0 1 1	0	2 1 1 1	0
0 1 0 0	0	3 0 0 0	0
0 1 0 1	1	3 0 0 1	0
0 1 1 0	0	3 0 1 0	0
0 1 1 1	0	3 0 1 1	0
1 0 0 0	0	3 1 0 0	0
1 0 0 1	1	3 1 0 1	0
1 0 1 0	0	3 1 1 0	0
1 0 1 1	0	3 1 1 1	0
1 1 0 0	0	4 0 0 0	0
1 1 0 1	1	4 0 0 1	1
1 1 1 0	0	4 0 1 0	0
1 1 1 1	0	4 0 1 1	0
2 0 0 0	0	4 1 0 0	0
2 0 0 1	1	4 1 0 1	1
2 0 1 0	0	4 1 1 0	0
2 0 1 1	0	4 1 1 1	0

0 0 0 0	0
0 0 0 1	1
0 1 0 0	0
0 1 0 1	1
1 0 0 0	0
1 0 0 1	1
1 1 0 0	0
1 1 0 1	1
2 0 0 0	0
2 0 0 1	1
2 1 0 0	0
2 1 0 1	1
4 0 0 0	0
4 0 0 1	1
4 1 0 0	0
4 1 0 1	1
4 1 1 1	0

0 0 4 1	**0**
0 1 2 1	**1**
0 1 3 1	**0**
0 1 4 1	**1**
1 1 4 1	**0**

Optimal KBM2L
(5 items)
[HP,HC,CS,BD]

KBM2L (17 items)
[CS,BD,HC,HP]

DST (40 cases) [CS,BD,HC,HP]

Results: Optimal Decision Tables and KBM2L List

HT: [HP,HC,CS,BD], 40 cases, 5 items

3 items – HT=No, 2 items – HT=Yes

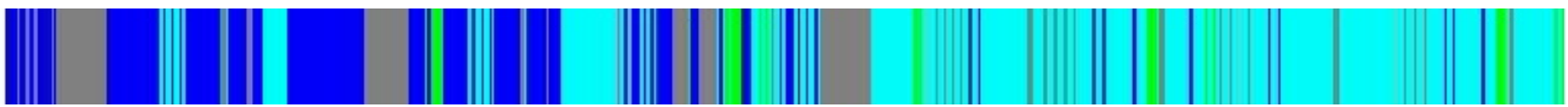
S: [CP,GHS,BD,CS,HC,HP,HT], 960 cases, 21 items

11 items – S=None, 10 items – S=Curative

CTRTS: [GHS,S,HT,CS,BD,HC,HP,CP], 2880 cases, 218 items

49 items – CTRTS=None, 69 items – CTRTS=Radio,

85 items – CTRTS=Chemo, 15 items – CTRS=Ch.Next.Rad



By means of the Variable Neighbourhood algorithm,
the same cases are now arranged in fewer items

Results: The global KBM2L for the gastric NHL protocol

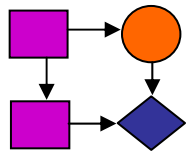
(HT, S, CTRTS): B_0[BD,HP,GHS,CS,CP,HC] 340 items

(HT, S, CTRTS): B_f[HP,HC,CP,CS,BD,GHS] 195 items

(HT,S,CTRS)	B_0	B_f
No, None, None	12	7
No, None, Radio	44	31
No, None, Chemo	88	40
No,Curative,None	41	26
No,Curative,Radio	44	34
No,Curative,Chemo	11	13
No,Curative,Ch.Next.Rad	4	4

(HT,S,CTRS)	B_0	B_f
Yes, None,None	3	1
Yes,None,Radio	34	13
Yes,None,Chemo	27	9
Yes,Curative,None	22	10
Yes,Curative,Radio	7	6
Yes,Curative,Chemo	3	1

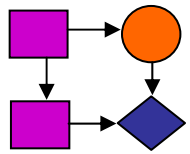
The items in the optimal lists are the rules of the clinical protocol



•The difference between rule 80 (1 case) and 81 (1 case), CTRTS, can be explained by the GHS value, Average and Good.

...	...
80	⟨*HP*: Absent, *HC*: High.Grade, *CP*: Perforation, *CS*: IV, *BD*: No, *GHS*: Average, (*HT*: No, *S*: Curative, *CTRTS*: Chemo)⟩
81	⟨*HP*: Absent, *HC*: High.Grade, *CP*: Perforation, *CS*: IV, *BD*: No, *GHS*: Good, (*HT*: No, *S*: Curative, *CTRTS*: Ch.Next.Rad)⟩
...	...
125	⟨*HP*: Present, *HC*: Low.Grade, *CP*: Perforation, *CS*:III, *BD*: No, *GHS*: Good, (*HT*: No, *S*: Curative, *CTRTS*: Chemo)⟩
126	⟨*HP*: Present, *HC*: Low.Grade, *CP*: Perforation, *CS*:IV, *BD*: Yes, *GHS*: Good, (*HT*: Yes, *S*: None, *CTRTS*: None)⟩
127	⟨*HP*: Present, *HC*: Low.Grade, *CP*: Perforation, *CS*: IV, *BD*: No, *GHS*: Good, (*HT*: Yes, *S*: Curative, *CTRTS*: Chemo)⟩
...	...

•The difference between rules 125 (3 cases) and 127 (3 cases), HT, can be explained by the CS value, III and IV. GHS is not relevant



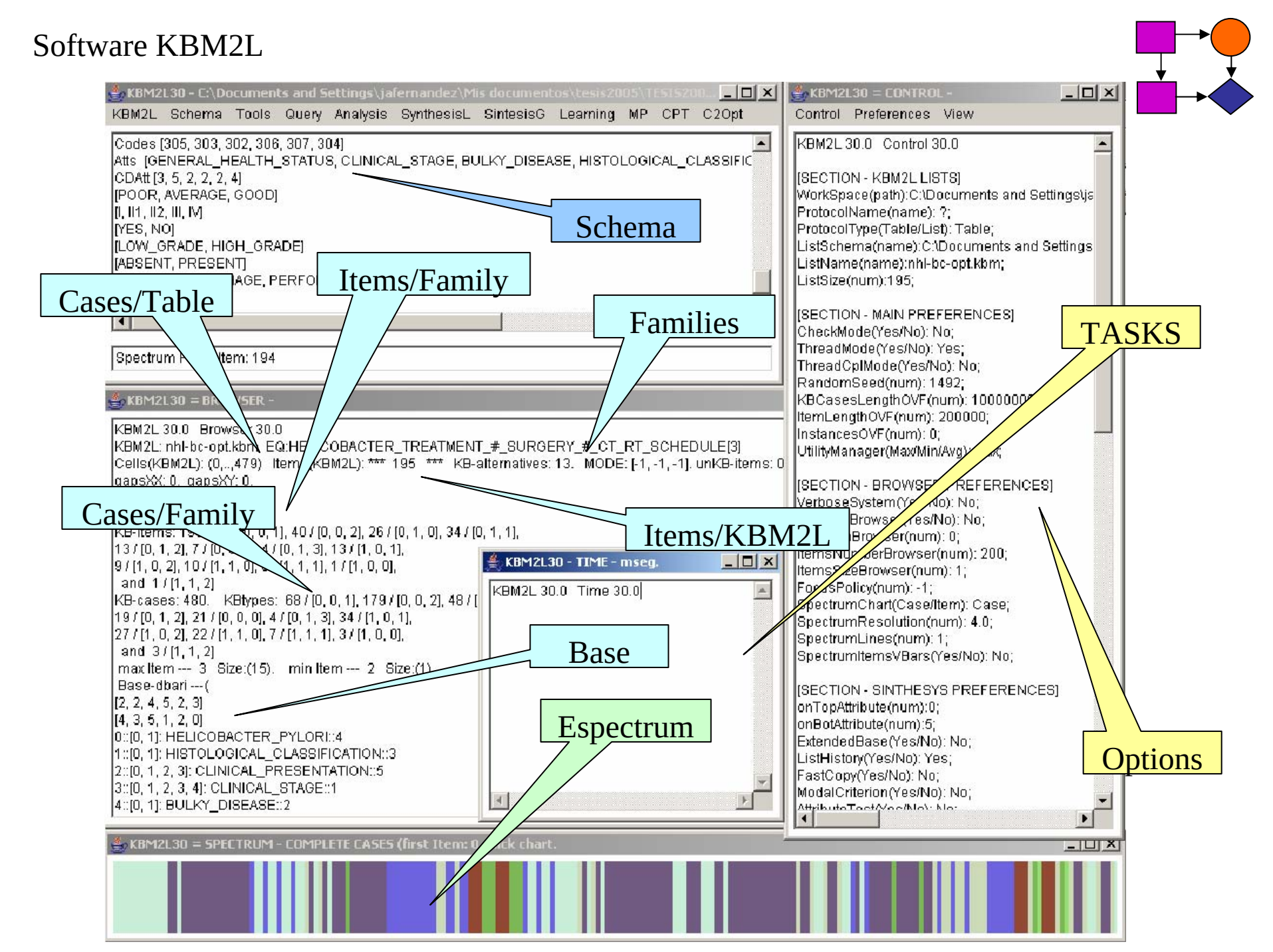
Focusing on one treatment, a new organisation is sought distinguishing only a pair of possible treatments T and ¬T.

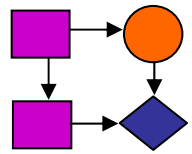
•Four ITEMS with (HT: No, S: Curative, CTRTS: Ch.Next.Rad) are grouped on a new base [GHS,HC,CP,BD,CS,HP] in one ITEM (12 cases) and are explained by GHS (Good), HC (High.Grade), CP (Perforation) and BD (No).

...	...
80	⟨*HP*: Absent, *HC*: High.Grade, *CP*: Perforation, *CS*: IV, *BD*: No, *GHS*: Average, (*HT*: No, *S*: Curative, *CTRTS*: Chemo)⟩
81	⟨*HP*: Absent, *HC*: High.Grade, *CP*: Perforation, *CS*: IV, *BD*: No, *GHS*: Good, (*HT*: No, *S*: Curative, *CTRTS*: Ch.Next.Rad)⟩
...	...

•Rule 3 (15 cases) say (HT: No, S: None, CTRTS: Chemo) because HP is Absent, HC is Low.Grade, CP is None and CS is II2, III or IV.
Variables BD and GHS are not relevant

Software KBM2L





Conclusion

- A good organisation of such tables reduces the memory required to store them.
- Also finds out which key attributes are able to explain the treatment suggestions.
- Explanations are useful during the refinement of the influence diagram
- In the future we will use this framework to perform Sensitivity Analysis

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Explaining Clinical Decisions by Extracting Regularity Patterns

Thank You
Any Questions?