A Comparison of Three Different Methods for Acquiring Knowledge about Virological Hepatitis Tests¹

Petr Berka²

Austrian Research Institute for Artificial Intelligence Schottengasse 3, A-1010 Vienna, Austria e-mail: berka@ai.univie.ac.at

Abstract

We present a comparison of Knowledge Seeker, CN2 and Knowledge EXplorer based on a real problem domain, interpretation of virological hepatitis tests. The problem domain can be divided into 6 subdomains, where the knowledge can be acquired separately. Unlike classical machine learning problems the goal classes are not mutually exclusive. The information how to classify contradictory examples was not available for the systems during learning. So the key question was how the systems handle ambiguity in data. Although each system uses different approach, there was no significant difference in the results of testing of acquired rules done for each subdomain separately.

Testing in the whole hepatitis domain was done only for Knowledge EXplorer because only this system can predict multiple classes. The results of testing are poorer then results obtained in the separate subdomains but can be improved by using some additional expert's knowledge.

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²Address for correspondence:

Dept. of Information and Knowledge Engineering, Prague University of Economics,

W. Churchill Sq. 4, 130 67 Prague, CR

e-mail: berka@nb.vse.cs

1 Introduction

To evaluate the possibility of automated knowledge acquisition in the virological domain, the problem of hepatitis was selected. This is a good defined problem, where three types of hepatititis, HAV, HB and HCV are evaluated according to six tests: AAK, AGM, CAK, HCK, SAG, SAK. The hepatitis problem domain can even be divided into three independent subdomains:

- HAV depends only on AAK and AGM,
- HB depends only on CAK, SAG and SAK,
- HCV depends only on HCK.

The classes to be learned can be divided into two groups:

- statements about diagnoses,
- statements about further treatments (recommendations of next tests).

So the data can be divided into six subsets schematically shown as follows:



The values of test results of all six tests are given in form of linguistic variables with following meaning:

p positive (5,=,p)
n negative (2,=,n)
l extremely negative (2,<,g)
g extremely positive (5,<,g)
X not measured</pre>

The list of all 32 classes is shown in the Appendix A.

The task is to find rules which can be used for consultation about hepatitis A, B and C diagnosis for a new patient. More than one diagnostic statement can be valid for a single case (e.g. *not imun* and *no infection*). This is complicated by the fact, that sometimes the expert is interested in the infection, sometimes in the immunity of an pacient. It depends on the aditional information, the clinical problem solved during the consultation. This information has not been used during learning.

2 Data preprocessing

From the original data set only examples with results for the tests AAK, AGM, CAK, HCK, SAG and SAK were selected. Then we eliminate examples with wrong type of virus and some examples marked by the expert. Thus we obtained 4339 examples which were divided into training set (first 1000 objects) and a testing set (the rest 3339 objects).

Both training and testing set were then divided into 6 subsets according to the subdomain as described above (HAV diagnosis, HAV recommendation, HB diagnosis, HB recommendation, HCV diagnosis, HCV recommendation). In every subset only corresponding input attributes were used. If no diagnostic statement was given for an example within specific subset, this example was assigned to the class 36 (no statement). The number of such "unclassified" examples was usually very high:

	HAV_d	HB_d	HCV_d	HAV_r	HB _ r	HCV_r
unclassified	336	308	912	998	926	221

Further preprocessing was done to unify the coding of resulting diagnoses and to remove the code of clinical problem.

3 Knowledge acquisition

The systems were running for each of the six subsets separately. We use standard setting of parameters in all three systems, so no additional background knowledge was used.

We will demostrate the functionality of every system on the HAV diagnosis subset. In this domain only the tests AAK and AGM are used as input attributes. Relevant diagnoses are:

a	1/HAV	Infection A
b	3/HAV	Immune A
с	6/HAV	Not Immune A
d	15/HAV	No Infection A
р	36	No statement

3.1 KnowledgeSeeker

KnowledgeSeeker is a TDIDT family system distributed by FirstMark Technologies Ltd. [7]. The algorithm can work with both symbolic and numeric data, it performes non incremental multiple concept learning. The system induces decision tree but allows to transform it into rules either in generic form or in Prolog. The Prolog rules can be used for consultation.

KnowledgeSeeker recursively splits each subset (node) into k new nodes starting with all observations at the initial node. This process continues until no more significant splits can be found. At each node all predictor (input) variables are considered in turn as candidates to split the node. The 'best' k-way split of each variable is found, then the significance of that split is used to rank variables on how well they split the node. The decision tree for HAV_d domain looks like follows:

	Legend				
	diagnosis 1	breakdown			
	a		1.0%		
	b		39.8%		
	с		1.1%		
	d		24.5%		
	р		33.6%		
	total		1000		
			AGM		
	Х			n	р
	g				
					1100.0%
				56.6%	
	2.7%			0.4%	0.0%
	2.7%			35.3%	0.0%
	0.7%			7.7%	0.0%
	94.0%			689	10
	301				
				AAK	
	AAK				
			g	n	р
Х	n	р	Х		
				0.0%	0.0%
0.0%	0.0%	0.0%	0.0%		91.1%
0.4%	0.0%	70.0%	0.0%	1.2%	0.0%
0.0%	61.5%	0.0%	0.0%	91.7 %	1.4%
0.0%	15.4%	0.0%	66.7 %	7.1%	7.5%
99.6%	23.1%	30.0%	33.3%	252	428
278	13	10	9		

In every node, relative number of examples for every goal class is given. The last number in every node is the number of covered examples. From this tree, Knowledge Seeker creates so called *generic rules* which corresponds to paths from the root to the leaves. In the THEN part of a rule, only goals with nonzero number of covered examples appear. Multiple conclusions in one rule indicate contradictory examples in the training set.

RULE_1	IF	
	AGM = X or g	
	AAK = X	
THEN	Diagnosis = b	0.4%
	Diagnosis = p	99.6%

```
RULE_2 IF
         AGM = X \text{ or } g
         AAK = n
THEN
         Diagnosis = c
                              61.5%
         Diagnosis = d
                              15.4%
         Diagnosis = p
                              23.1%
RULE_3 IF
         AGM = X \text{ or } g
         AAK = p
         Diagnosis = b
THEN
                              70.0%
         Diagnosis = p
                              30.0%
RULE_4 IF
         AGM = n
         AAK = g \text{ or } X
         Diagnosis = d
THEN
                              66.7%
         Diagnosis = p
                              33.3%
RULE_5 IF
         AGM = n
         AAK = n
         Diagnosis = c
                               1.2%
THEN
         Diagnosis = d
                              91.7%
         Diagnosis = p
                               7.1%
RULE_6 IF
         AGM = n
         AAK = p
         Diagnosis = b
THEN
                              91.1%
         Diagnosis = d
                               1.4%
                               7.5%
         Diagnosis = p
RULE 7 IF
         AGM = p
THEN
                             100.0%
         Diagnosis = a
```

Notice the disjunction of values for the tests. KnowledgeSeeker makes this grouping during tree creation.

The Prolog rules are created for *each node* in the tree. So consultation can be done even for examples with some missing input values:

```
ks_rule_base(rule(1, [cond(AGM='X '; AGM='g ')], 'p ')).
ks_rule_base(rule(2, [cond(AGM='X '; AGM='g '), cond(AAK='X ')], 'p ')).
ks_rule_base(rule(3, [cond(AGM='X '; AGM='g '), cond(AAK='n ')], 'c ')).
ks_rule_base(rule(4, [cond(AGM='X '; AGM='g '), cond(AAK='p ')], 'b ')).
ks_rule_base(rule(5, [cond(AGM='n ')], 'b ')).
```

```
ks_rule_base(rule(6, [cond(AGM='n '), cond(AAK='+ '; AAK='X ')], 'd ')).
ks_rule_base(rule(7, [cond(AGM='n '), cond(AAK='n ')], 'd ')).
ks_rule_base(rule(8, [cond(AGM='n '), cond(AAK='p ')], 'b ')).
ks_rule_base(rule(9, [cond(AGM='p ')], 'a ')).
ks_rule_base(rule(10, [], 'b ')).
```

In this rules, the ambiguity dissapears, since only the most frequent goal category is used as the conclusion. The last rule corresponds to the root of the tree (*default rule*), so during consultation every example is classified. The Prolog rules can be used for consultations with inference mechanism supplied by the system. When consulting for the case AAK = n & AGM = n, the result will be d (15/HAV) (from the rule no. 7).

3.2 CN2

CN2 is a system of the AQ family [4]. It induces decision rules from given examples. The system performes non incremental multiple concept learning. Unlike standard AQ, CN2 can work with noisy data.

CN2 works in an iterative way each step generating a rule and then removing the examples the rule covers from the training set. In each iteration the system searches for a complex (rule) covering a large number of remaining examples of a single class C and few of other classes. This process stops when no more satisfactory complexes can be found. The system searches for complexes by carrying out a pruned general-to-specific search. A complex is specialized by either adding a new conjunctive term or removing a disjunctive element in one of its selectors.

CN2 creates unordered or ordered set of rules. Unordered rules require some numerical confidence measure to handle possible clashes. Within an ordered list of rules clashes cannot occur, because each rule in the list has precedence on all subsequent rules.

The system generates decision rules for each class separately. When learning ordered set of rules the class predicted by each rule is the majority class among the covered examples. When learning unordered set of rules, a rule, which gives better then average prediction of a rare-occurring class can be created, too. So the resulting knowledge base can contain contradictory rules:

```
*UNORDERED-RULE-LIST*
```

```
ΙF
      SER_ELH_AGM = p
THEN
     Diagnosis = 1/HAV
                         [10 0 0 0 0]
IF
      SER_ELH_AAK = p
  AND SER_ELH_AGM = n
                         [0 390 0 6 32]
THEN
     Diagnosis = 3/HAV
IF
      SER_ELH_AAK = p
  AND SER_ELH_AGM = X
THEN Diagnosis = 3/HAV
                         [07002]
```

```
IF
      SER_ELH_AAK = n
  AND SER_ELH_AGM = X
                         [0 0 8 2 3]
THEN Diagnosis = 6/HAV
IF
      SER_ELH_AAK = n
  AND SER_ELH_AGM = n
                         [0 0 3 231 18]
THEN
     Diagnosis = 6/HAV
ΙF
      SER_ELH_AAK = n
  AND SER_ELH_AGM = n
THEN Diagnosis = 15/HAV
                          [0 0 3 231 18]
ΙF
      SER_ELH_AAK = g
     Diagnosis = 15/HAV
                          [0 0 0 5 2]
THEN
IF
      SER_ELH_AAK = X
  AND SER_ELH_AGM = n
                          [0 0 0 1 1]
THEN Diagnosis = 15/HAV
IF
      SER_ELH_AAK = X
  AND SER_ELH_AGM = X
THEN
      Diagnosis = 36 [0 1 0 0 277]
ΙF
      SER_ELH_AGM = g
      Diagnosis = 36 [0 0 0 0 1]
THEN
IF
      SER_ELH_AAK = X
  AND SER_ELH_AGM = n
THEN Diagnosis = 36 [0 0 0 1 1]
```

```
(DEFAULT) Diagnosis = 3/HAV [10 398 11 245 336]
```

The list of numbers in the square brackets gives (for each class) the number of examples covered by the rule.

When consulting for the case AAK = n & AGM = n, the result will be 15/HAV (from the rule no. 6).

3.3 Knowledge EXplorer

Knowledge EXplorer has been developed at the Prague School of Economics [1, 6]. The system performs symbolic empirical multiple concept learning from examples, where the induced concept description is of the form of weighted decision rules. The algorithm can deal with noisy data, unknown values, redundancy and contradictions.

Knowledge EXplorer works in an iterative way each iteration testing and expanding an implication $Ant \Longrightarrow C^*$. This process starts with "default rule" with weight computed

from the relative frequency of C^* in data and stops after testing all implications which were created according to user defined criteria. The implications are evaluated according to decreasing frequency of Ant, so most reliable implications are tested first. During testing, the validity (conditional probability $P(C^*/Ant)$) of an implication is computed. If this validity significantly differs from the composed weight (value obtained when composing weights of all subrules of the implication $Ant \implies C^*$), then this implication is added to the knowledge base. The weight of this new rule is computed from the validity and the composed weight using inverse composing function. For composing weights PROSPEC-TOR's [5] combining function is used. During expanding, new implications are created by adding single categories to Ant.

Unlike AQ-like systems, Knowledge EXplorer does not remove covered examples from the training data set. So more than one rule can be learned for the same class from an example.

Knowledge EXplorer displays the weighted rules together with the number of examples which fulfil the left-hand side, the number of examples which fulfil the right-hand side of the rule and with the number of examples which fulfil both sides of the rule. So the last number corresponds to the number given by CN2.

		ED RULES						
	Fr	equenci	es					
no.	left	right	both	Weight	Imp	lica	ti	on
1	1000	10	10	0.0250	0-	==>		/a.
2	1000	398	398	0.6237	0-	==>		7b
3	1000	11	11	0.0275	0-	==>		7c
4	1000	245	245	0.5281	0 -	==>		7d
5	1000	336	336	0.5850	0-	==>		7р
6	689	10	0	0.0275	2n	==>		7a
7	689	398	390	0.6184	2n	==>		7Ъ
8	689	11	3	0.2802	2n	==>		7c
9	689	245	243	0.5680	2n	==>		7d
10	689	336	53	0.1445	2n	==>		7p
11	448	10	10	0.6974	1p	==>		7a
12	448	398	397	0.8873	1p	==>		7Ъ
13	448	11	0	0.0380	1p	==>		7c
14	448	245	6	0.0300	1p	==>		7d
15	448	336	35	0.1469	1p	==>		7p
16	428	10	0	0.4112	1p2	'n =	=>	7a
17	428	398	390	0.4458	1p2	'n =:	=>	7b
18	428	11	0	0.7290	1p2	'n =:	=>	7c
19	428	245	6	0.4436	1p2	'n =:	=>	7d
20	428	336	32	0.8487	1p2	'n =:	=>	7p
21	300	10	0	0.0610	2X	==>		7a
22	300	398	8	0.0413	2X	==>		7b
23	300	11	8	0.7164	2X	==>		7c
24	300	245	2	0.0149	2X	==>		7d

25	300	336	282	0.9479	2X =:	=>	7p
26	280	10	0	0.0651	1X =:	=>	7a
27	280	398	1	0.0054	1X =:	=>	7b
28	280	11	0	0.0594	1X =:	=>	7c
29	280	245	1	0.0080	1X =:	=>	7d
30	280	336	278	0.9937	1X =:	=>	7p
31	265	10	0	0.0685	1n =:	=>	7a
32	265	398	0	0.0011	1n =:	=>	7b
33	265	11	11	0.8037	1n =:	=>	7c
34	265	245	233	0.9163	1n =:	=>	7d
35	265	336	21	0.1491	1n =:	=>	7p
36	252	10	0	0.9738	1n2n	==>	7a
37	252	398	0	0.3935	1n2n	==>	• 7b
38	252	11	3	0.4050	1n2n	==>	• 7c
39	252	245	231	0.5305	1n2n	==>	• 7d
40	252	336	18	0.8390	1n2n	==>	• 7p
41	13	10	0	0.9968	1n2X	==>	- 7a
42	13	398	0	0.9979	1n2X	==>	• 7b
43	13	11	8	0.9153	1n2X	==>	• 7c
44	13	245	2	0.7711	1n2X	==>	• 7d
45	13	336	3	0.1936	1n2X	==>	• 7p
46	10	10	10	0.9987	2p =:	=>	7a
47	10	398	0	0.0293	2p =:	=>	7b
48	10	11	0	0.6388	2p =:	=>	7c
49	10	245	0	0.0428	2p =:	=>	7d
50	10	336	0	0.0343	2p =:	=>	7p
51	9	10	0	0.9353	2X1p	==>	• 7a
52	9	398	7	0.9168	2X1p	==>	• 7b
53	9	11	0	0.9517	2X1p	==>	• 7c
54	9	245	0	0.9906	2X1p	==>	• 7d
55	9	336	2	0.1930	2X1p	==>	• 7p
56	2	10	0	0.9998	1X2n	==>	7a
57	2	398	0	0.9448	1X2n	==>	• 7b
58	2	11	0	0.9972	1X2n	==>	• 7c
59	2	245	1	0.9946	1X2n	==>	• 7d
60	2	336	1	0.0552	1X2n	==>	• 7p

0 in the rule denotes default, 1 denotes AAK, 2 denotes AGM and 7 denotes the diagnosis. Knowledge EXplorer creates for every goal category a single rule, so in HAV_d domain a group of 5 rules with the same left-hand side corresponds to one rule created by CN2. Since weights are not relative frequencies, the sum of the weights within such a group of rules does not equal to 1. So more then one goal concept can be predicted during consultation.

The acquired knowledge base can be used for consultation or testing. In both cases weights of *all* classes are computed for the given case using PROSPECTOR combining function: $x \oplus y = (x * y)/(x * y + (1 - x) * (1 - y))$.

The resulting weights are in the range $\langle 0, 1 \rangle$. Weight = 0.5 indicates undecided, weight \rangle 0.5 indicates class predicted and weight \langle 0.5 indicates class not predicted. For a single example, resulting weight can be greater than 0.5 for more then one class. During consultation, all such classes are given out as the result, during testing the class with highest weight is the predicted result.

When consulting for the case AAK = n & AGM = n, using rules (1-5) (default rule), (6-9), (31-35) and (35-40), the resulting weights of all classes will be

 no.	goal	weight	object
 1.	7a	0.0020	nn??????
	7b	0.0019	
	7c	0.0298	
	7d	0.9479	
	7p	0.1786	

So in this case the predicted concept will be d (15/HAV) both during consultation and testing.

Using Knowledge EXplorer we have created a second, *alternative knowledge base*. This knowledge base differs from the standard one described above in three user defined criteria which may better correspond to decision making done by expert:

- 1. only rules for all tests within the domain are created ("full length" rules),
- 2. only rules for nonzero number of examples are created,
- 3. the default rule is not used.

Because of (1) and (3) the resulting knowledge base will now consist of *independent* rules, each corresponding to one (or group of same) examples.

We present the rules learned in the HAV_domain in more legible form:

RULE	1:	IF	AAK == positive	
		AND	AGM == negative	
		THEN	Diagnosis == 3/HAV	(0.9445)
			Diagnosis == 15/HAV	(0.0350)
			Diagnosis == 36	(0.1869)
RULE	2:	IF	AAK == not measured	
		AND	AGM == not measured	
		THEN	Diagnosis == 3/HAV	(0.0090)
			Diagnosis == 36	(0.9978)
RULE	3:	IF	AAK == negative	
		AND	AGM == negative	
		THEN	Diagnosis == 6/HAV	(0.0298)
			Diagnosis == 15/HAV	(0.9479)
			Diagnosis == 36	(0.1786)

RULE 4: ΙF AAK == negative AGM == not measured AND (0.7596)THEN Diagnosis == 6/HAV Diagnosis == 15/HAV (0.3846)(0.5192)Diagnosis == 36 RULE 5: ΙF AGM == positive AND AAK == positive THEN Diagnosis == 1/HAV (0.9524)AGM RULE 6: IF == not measured AAK == AND positive (0.8611)THEN Diagnosis == 3/HAV (0.5139)Diagnosis == 36 RULE 7: ΙF AAK extremely positie == AND AGM == negative (0.8214)THEN Diagnosis == 15/HAV Diagnosis == 36 (0.5536)RULE IF 8: AAK == not measured AGM == negative AND THEN Diagnosis == 15/HAV (0.6875)Diagnosis == 36 (0.6875)RULE 9: ΙF AGM == extremely positive AND AAK positive == THEN Diagnosis == 36 (0.6667)

During consultation, only one rule (group of rules with the same left-hand side) will be applicable for an example and the resulting weights of all classes will correspond to weights in the rule (or to 0.5 if the class does not appear in the rule). In our case, the predicted class is again d (15/HAV) (with the weight 0.9479 from the rule no. 3).

3.4 Summary of the learning step

All three systems can work with noisy data and contradictions. The created rules contain this information; Knowledge Seeker and Knowledge EXplorer in the form of multiple conclusions in the rules (this is always done), CN2 may create "contradictory" rule for rare occurred examples (done if such rule gives better then average prediction).

Neither Knowledge Seeker, nor CN2 use this information during consultations. Both systems assign a contradictory example to the majority class. Knowledge EXplorer's inference mechanism computes weights for *all clases*, so it can assign a contradictory example to more than one class. In the HAV_d domain the class *no statement (36)* will be very often predicted together with another diagosis (see rules 4, 6, 7, 8 in the alternative knowledge base). An example of more interesting multiple diagnosis rule is taken from

the HB_d domain:

RULE	19:	IF	CAK	==	extre	mely posi	ltive
		AND	SAK	==	extre	mely posi	ltive
		AND	SAG	==	negat	ive	
		THEN	Diag	nosis	; ==	З/НВ	(0.5982)
			Diag	nosis	; ==	15/HB	(0.5179)
			Diag	nosis	; ==	26/HB	(0.5179)
			Diag	nosis	; ==	36	(0.6786)

where 3/HB stands for *immune* B, 15/HB stands for *no infection* B and 26/HB stands for *possibly immune* B. During consultation, the result will be *all four diagnoses*, during testing, the result will be *36*. The question of contradictions or multiple diagnoses has to be solved by additional analysis. In the hepatitis domain, this can be done using information about clinical problem.

During consultation, only one rule is activated in Knowledge Seeker or CN2 whereas Knowledge EXplorer combines (running standard knowledge base) a number of applicable rules using PROSPECTOR like inference mechanism.

Using Knowledge EXplorer we learn two different knowledge bases. The *alternative* knowledge base is very modular, transparent and easy to update since the rules do not interact. When consulting, "perfect match" is required, so some examples may be left unclassified. This indicates a missing rule which can be (after verification by expert) simply added to the knowledge base. So knowledge base actualisation in this case does not require learning from an expanded training set.

4 Testing

Testing was done using 3339 examples, not seen during learning phase. At first, we test in the six domains separately. The results are given as relative number of correctly classified examples. We will again describe in more details the results for the HAV_d domain.

4.1 Knowledge Seeker

RESUL	TS OF T	ESTING					
Value		Right			Wrong		Total
b	1252	99.44	%	7	0.56	%	1259
р	988	80.52	%	239	19.48	%	1227
d	761	96.33	%	29	3.67	%	790
a	37	100.00	%	0	0.00	%	37
с	12	46.15	%	14	53.85	%	26
Altogether	3050	91.34	%	289	8.66	%	3339

For each class found in data, the number of correct and incorrect classifications is given in the table.

4.2 CN2

PREDICTED					
_1_HAV	_3_HAV	_6_HAV	_15_HAV	7_36	Accuracy
37	0	0	0	0	100.0 %
1	1251	0	5	2	99.4 %
0	1	12	13	0	46.2 %
0	16	9	761	4	96.3 %
5 1	110	10	106	1000	81.5 %
accuracy:	91.7 <mark>%</mark>				
accuracy:	37.7 %				
	PREDICTED _1_HAV 7 37 7 1 7 0 7 0 7 0 1 accuracy: accuracy:	PREDICTED _1_HAV _3_HAV 37 0 1 1251 0 1 0 16 1 110 accuracy: 91.7 % accuracy: 37.7 %	PREDICTED _1_HAV _3_HAV _6_HAV 37 0 0 1 1251 0 0 1 12 0 16 9 1 110 10 accuracy: 91.7 % accuracy: 37.7 %	PREDICTED $_1$ _HAV $_3$ _HAV $_6$ _HAV $_15$ _HAV 37 0 0 0 1 1251 0 5 7 0 1 12 13 7 0 16 9 761 4 1 110 10 106 accuracy: 91.7 % 37.7 % 37.7 %	PREDICTED $_1_HAV$ $_3_HAV$ $_6_HAV$ $_{15_HAV}$ $_{36}$ $_37$ 0 0 0 0 $_1$ 1251 0 5 2 $_0$ 1 12 13 0 $_0$ 16 9 761 4 $_1$ 110 10 106 1000 accuracy: 91.7 % 4 4 4

The number in row i, column j is the number of examples classified as class j which really belongs to class i. Default accuracy is the accuracy of the default rule (all examples classified to most frequent class).

4.3 Knowledge EXplorer

We present testing results for the standard knowledge base (first table) and for the alternative knowledge base (second table).

			RESULI	S OF RULE	BASE TESTI	ING				
	pred	pred total		from	which	total	from	from which		
		abs	rel	true	false		true	false		
	 7a	39	 1%	37	2	100%	95%	5%		
	7b	1398	42%	1253	145	100%	90 %	10%		
	7c	31	1%	12	19	100%	39%	61%		
	7d	872	26%	756	116	100%	87 %	13%		
	7p	999	30 %	992	7	100%	99%	1%		
	Total	3339	100%	3050	289	100%	91%	9%		
not	decided	0	0%	*******	******	··	*******	******		
not	predict.	0	0%	******	********	<***********	* * * * * * * * *	******		
	Total	3339	100%	3050	289	100%	91%	 9%		

			RESULI	IS OF RULE	BASE TESTI	NG		
	pred	total		from	from which		from which	
		abs	rel	true	false		true	false
	 7a	39	1%	37	2	100%	95%	 5%
	7b	1377	41%	1250	127	100%	91%	9%
	7c	31	1%	12	19	100%	39%	61%
	7d	878	26%	759	119	100%	86%	14%
	7p	1011	30%	1003	8	100%	99%	1%
	Total	3336	100%	3061	275	100%	92%	8%
not	decided	0	0%	*******	*****	*****	*******	******
not	predict.	3	0%	******	*******	*********	* * * * * * * * *	******
	Total	3339	100%	3061	275	100 %	92%	 8%

For every learned class (a row in the table) the number of classifications done by the system and the number of correct classifications is given. Some examples in the testing set may be unclassified; either all resulting weights were in the range < 0.45, 0.55 > (the row "not decided" in the table), or there was no applicable rule in the knowledge base (the row "not predict." in the table)³. The resulting performance of the system is given in the row "Total".

4.4 Summary of partial test results

The tables below summarises for every domain the results (number of generated rules, successfulness of testing) of all three systems. Percentages in brackets are the results of testing in training data. The umber of rules generated by Knowledge Seeker is given in the form *number_of_Prolog_rules (number_of_generic_rules)*, the umber of rules generated by Knowledge EXplorer is given in the form *total_number (number_of_different_left-hand_sides)*, so the first number is the number of rules used by the inference mechanism.

HAV diagnosis

	Rules	Correct	Incorrect	Not
	Generated	Classifications	Classifications	Classified
KnowledgeSeeker	10(7)	91.3% (92.9%)	8.7% (7.1%)	$0.0\% \ (0.0\%)$
m CN2	12	91.7%~(93.0%)	8.3%~(7.0%)	0.0%~(0.0%)
Knowledge Explorer std.	60(12)	91.3%~(92.4%)	8.7%~(7.6%)	0.0%~(0.0%)
Knowledge Explorer alt.	19(9)	91.7%~(93.0%)	8.2%~(7.0%)	0.1%~(0.0%)

³If the knowledge base contains default rule, prediction is always done.

		0			
	Rules	Correct	Incorrect	Not	
	Generated	Classifications	Classifications	Classified	
KnowledgeSeeker	19(13)	90.3%~(91.5%)	9.7%~(8.5%)	0.0%~(0.0%)	
$\overline{\text{CN2}}$	30	88.6%~(89.9%)	11.4% (10.1%)	0.0%~(0.0%)	
Knowledge Explorer std.	216(24)	89.8%~(90.5%)	9.1% (9.1%)	$1.1\% \ (0.4\%)$	
Knowledge Explorer alt.	48 (30)	90.1% (92.1%)	8.8% $(7.8%)$	1.1% (0.1%)	
HCV diagnosis					
	Rules	Correct	Incorrect	Not	
	Generated	Classifications	Classifications	Classified	
KnowledgeSeeker	4(3)	94.6% (100.0%)	$5.4\% \ (0.0\%)$	0.0%~(0.0%)	
$\overline{\text{CN2}}$	6	94.6% (100.0%)	5.4%~(0.0%)	$0.0\% \; (0.0\%)$	
Knowledge Explorer std.	15(5)	94.6% (100.0%)	5.4%~(0.0%)	0.0%~(0.0%)	
Knowledge Explorer alt.	5(5)	94.5% (100.0%)	5.4%~(0.0%)	0.1%~(0.0%)	
	HAV reco	mmendation			
	Rules	Correct	Incorrect	Not	
	Generated	Classifications	Classifications	Classified	
KnowledgeSeeker	1(0)	99.6%~(99.8%)	0.4%~(0.2%)	0.0%~(0.0%)	
m CN2	7	99.6%~(99.8%)	0.4%~(0.2%)	0.0%~(0.0%)	
Knowledge Explorer std.	4(2)	99.6%~(99.8%)	0.4%~(0.2%)	0.0%~(0.0%)	
Knowledge Explorer alt.	10 (9)	99.6%~(99.8%)	0.3%~(0.2%)	0.1%~(0.0%)	
HB recommendation					
	Rules	Correct	Incorrect	Not	
	Generated	Classifications	Classifications	Classified	
KnowledgeSeeker	14(9)	96.3%~(97.7%)	3.7%~(2.3%)	$0.0\% \; (0.0\%)$	
m CN2	18	93.1%~(93.0%)	6.9%~(7.0%)	0.0%~(0.0%)	
Knowledge Explorer std.	187(17)	95.7%~(94.9%)	4.3%~(5.1%)	0.0%~(0.0%)	
Knowledge Explorer alt.	39(30)	95.6%~(97.8%)	3.3%~(2.1%)	1.1%~(0.0%)	
HCV recommendation					
Rules Correct Inco			Incorrect	Not	
	Generated	Classifications	Classifications	Classified	
KnowledgeSeeker	5(4)	78.4%~(86.8%)	21.6% (13.2%)	0.0%~(0.0%)	
m CN2	8	78.4%~(86.8%)	21.6%~(13.2%)	0.0%~(0.0%)	
Knowledge Explorer std.	12(4)	78.2%~(86.6%)	21.8%~(13.4%)	0.0%~(0.0%)	
Knowledge Explorer alt.	10(5)	78.5%~(86.6%)	21.4% (13.4%)	0.1%~(0.0%)	

HB diagnosis

Within every domain, there is no great difference in performance of the used systems. Poor results in the HCV_r domain are caused by very noisy training set (missing recommendations).

The successfulness of the systems in the six subsets looks impresive but must be interpreted very carefully. Because of the high number of "class = 36" examples, simply using the default rule the system will reach 91.2%, 99.8% and 92.6% of correctly classified examples in training set for the HCV_d, HAV_r and HB_r domain, respectively. (Only the default rule was used by all systems for prediction in the HAV_r domain. In the HCV_d domain, although the class 1/HCV was changed to 34/HCV in the testing set and so corresponding examples were not classified correctly, the total successfulness is still very high.) We also cannot simply average the partial results to evaluate the performance of the systems for the whole hepatitis problem domain.

4.5 Final testing

To test the performance on the whole problem domain we must compare the results of prediction of all six partial knowledge bases with the diagnoses given by the expert. Only Knowledge EXplorer was used for this testing because it can give multiple results during consultation.

At first, we combined the six knowledge bases into one. Then we run consultation with this knowledge base for the examples in training set and testing set. From the list of valid diagnoses found by the system for a single case we removed the diagnosis no statement. We count the number of examples, where all diagnostic statements given by the expert were found also by the system (we denote the diagnoses given by the system as *superset*) and the number of examples, where diagnoses given by the expert were equivalent to diagnoses found by the system (we denote both diagnoses lists *equivalent*).

The listing below shows results of testing for the first ten testing examples.

no.	object	EXPERT	SYSTEM	
1	pnnXnn	3/HAV+15/HB+10/HCV,32	15/HB+3/HAV+10/HCV	3/0 Sup Equ
2	pnnXnn	3/HAV+15/HB+10/HCV,42.32	15/HB+3/HAV+10/HCV	3/0 Sup Equ
3	pnnpnn	1/HCV,32.164.31	1/HCV+15/HB+3/HAV	1/2 Sup
4	pngnnn	22/HCV+15/HB+3/HAV,166.32	22/HCV+3/HAV 2/0	
5	pnnXnn	3/HAV+15/HB+10/HCV,32	15/HB+3/HAV+10/HCV	3/0 Sup Equ
6	pnnXnn	3/HAV+15/HB+10/HCV,30	15/HB+3/HAV+10/HCV	3/0 Sup Equ
7	nnnXnn	10/HCV+15/HAV+15/HB,111	15/HB+15/HAV+10/HCV	3/0 Sup Equ
8	pnpXnn	10/HCV+10/CGM+3/HAV,31	3/HAV+10/HCV+10/CGM	3/0 Sup Equ
9	nnnXnn	22/HCV+15/HAV+15/HB,111	15/HB+15/HAV+10/HCV	2/1
10	XXXnXX	22/HCV,240	22/HCV 1/0 Sup Equ	L

Each row in the listing shows input example, diagnoses given by expert (together with the number of question), results of the system, no. of correct decisions of the system, no. of incorrect decisions of the system, evaluation of the results (Sup for superset, Equ for equivalence). The summary of this testing is shown below:

```
standard knowledge base
training data = 1000, Superset = 931 (93.1%), Equivalence = 762 (76.2%)
testing data = 3339, Superset = 2930 (87.8%), Equivalence = 2305 (69.0%)
```

alternative knowledge base training data = 1000, Superset = 932 (93.2%), Equivalence = 784 (78.4%) testing data = 3339, Superset = 2933 (87.8%), Equivalence = 2367 (70.1%)

The resulting successfulness in the whole hepatitis domain is significantly lower then the successfulnes in separate domains. This is bacause of interactions between the six subdomains; if wrong prediction is done in one subdomain, then the total prediction is wrong. There is no great difference between standard and alternative knowledge base. Since the alternative knowledge base is easier to interpret and update, it seems to be better.

Ideally, in the training set the number of "supersets" should by the same as the number of objects since Knowledge EXplorer can learn rules with multiple valid conclusions. Because of the unregular distribution of examples for multiple classes, the weights computed for rare diagnoses were usually below 0.5 and so corresponding diagnoses were not predicted during consultation (e.g. 6/HAV for AAK = n & AGM = n). In the testing set this difference is naturally greater because some testing examples were not used during the learning process.

The difference between the number of equivalences and the number of supersets results from the fact, that in case of possible multiple diagnoses, only one was selected by the expert according to the clinical problem, whereas the system presents all valid diagnoses. Another reason is, that in expert's evaluation some "superdiagnosis" in one subdomain (typically *infection*) suppresses diagnoses in all other domains.

By adding this knowledge to learned rules, the total performance can be improved. The number of supersets can be increased by setting all multiple diagnoses as valid. This can be done in the alternative knowledge base by increasing the correponding weights. The number of equivalences can be increased by directly modifying the rules adding the clinical problem statement (e.g. if clinical problem = immunity and AAK = n and AGM = n then Diagnosis = 6/HAV), or processing the list of system's results after the consultation (e.g. if clinical problem = immunity then don't show diagnoses about infection). Further, it will be necessary to introduce rules to handle superdiagnoses. When doing this for the alternative knowledge base, we obtain following results:

no.of objects = 1000, Superset = 918 (91.8%), Equivalence = 812 (81.2%)
no.of objects = 3339, Superset = 2939 (88.0%), Equivalence = 2455 (73.5%)

5 Conclusion

We present a comparison of three different knowledge acquisition systems based on a real problem domain, interpretation of virological hepatitis tests. Unlike classical machine learning problems the goal classes in this domain are not mutually exclusive. The information how to classify contradictory examples was not available for the systems during learning. All three tested systems can learn in noisy domains but only Knowledge EXplorer uses the ambiguity of classes during consultation. During standard testing in separate subdomains all three systems gave similar (good) results.

The performance in the whole hepatitis domain is significantly lower. The acquired knowledge base must be verified and extended using additional expert knowledge about how to solve the ambiguities. This can be very easily done for the alternative knowledge base created by Knowledge EXplorer, since this knowledge base consists of independent rules each rule describing (within a subdomain) an complete example. This knowledge base can also be easily updated by adding rules for unclassified examples.

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A Data description

For every input attribute (tests AAK, AGM, CAK, HCK, SAG, SAK) following values are given:

```
p positive (5,=,p)
n negative (2,=,n)
l extremely negative (2,<,g)
g extremely positive (5,<,g)
X not measured</pre>
```

Output diagnosis has following valid values:

a	1/HAV	Infection A
b	3/HAV	Immune A
с	6/HAV	Not Immune A
d	15/HAV	No Infection A
е	1/HB	Infection B
f	З/НВ	Immune B
g	4/HB	Suspicion B
h	6/HB	Not Immune B
i	15/HB	No Infection B
j	26/HB	Possibly Immune B
k	27/HB	Successful vaccination B
1	29/HB	Vaccination? B
m	1/HCV	Infection C
n	4/HCV	Suspicion C
0	34/HCV	Possibly Infection C
р	36	No statement
q	10/HAV	Test A
r	10/AGM	Test AGM
s	10/HB	Test B
t	21/HB	Test 4 We B
u	10/CAK	Test CAK
v	10/SAG	Test SAG
ស	10/SAK	Test SAK
х	8/BVE	Test 2 We BVE
у	10/BVE	Test BVE
z	10/CGM	Test CGM
А	22/SAG	Test 2 Mo SAG
В	22/SAK	Test 2 Mo SAK
С	22/BVE	Test 2 Mo BVE
D	10/HCV	Test HCV
Е	22/HCV	Test 2 Mo HCV
F	41/HCV	Test PCR C

B Alternative knowledge base

The resulting Knowledge EXplorer knowledge base for the whole hepatitis problem domain was obtained by combining the partial knowledge bases learned in HAV_d, HB_d, HCV_d, HAV_r, HB_r and HCV_r subdomains. This listing shows the knowledge base without additional expert's knowledge.

RULES IN THE KNOWLEDGE BASE

RULE 1: IF SER-ELH-AAK == positive (5,=,p) AND SER-ELH-AGM == negative (2,=,n) '3/HAV' Immun A (0.9445)THEN Diagnosis == Diagnosis == '15/HAV' No Infection A (0.0350)(0.1869)Diagnosis == '36' No statement RULE 2: ΙF SER-ELH-AAK == not measured AND SER-ELH-AGM == not measured Diagnosis == '3/HAV' Immun A (0.0090)THEN (0.9978)Diagnosis == '36' No statement RULE ΙF SER-ELH-AAK == negative (2,=,n) 3: AND SER-ELH-AGM == negative (2,=,n) (0.0298)THEN Diagnosis == '6/HAV' Nicht immun A Diagnosis == '15/HAV' No Infection A (0.9479) Diagnosis == '36' No statement (0.1786)RULE 4: ΙF negative (2,=,n) SER-ELH-AAK == AND SER-ELH-AGM == not measured THEN Diagnosis '6/HAV' Nicht immun A (0.7596)== (0.3846)Diagnosis == '15/HAV' No Infection A No statement (0.5192)Diagnosis == '36' RULE 5: ΙF positive (5,=,p) SER-ELH-AGM == AND SER-ELH-AAK == positive (5,=,p) '1/HAV' Infection A THEN Diagnosis == (0.9524)RULE 6: ΙF SER-ELH-AGM == not measured SER-ELH-AAK == positive (5,=,p) AND Diagnosis == '3/HAV' Immun A THEN (0.8611)Diagnosis == '36' No statement (0.5139)RULE 7: ΙF SER-ELH-AAK == extremely positive (5,<,g) negative (2,=,n) SER-ELH-AGM == AND Diagnosis == '15/HAV' No Infection A THEN (0.8214)Diagnosis == '36' No statement (0.5536)

RULE 8: IF SER-ELH-AAK == not measured AND SER-ELH-AGM == negative (2,=,n) THEN Diagnosis == '15/HAV' No Infection A (0.6875) Diagnosis == '36' No statement (0.6875) RULE 9: IF SER-ELH-AGM == extremely positive (5,<,g)</pre> SER-ELH-AAK == positive (5,=,p) AND THEN Diagnosis == '36' No statement (0.6667) RULE 10: IF SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '6/HB' Not Immune B (0.0908) THEN Diagnosis == '15/HB' No Infection B (0.9556) Diagnosis == '36' No statement (0.2647) RULE 11: IF SER-ELH-CAK == not measured AND SER-ELH-SAK == not measured AND SER-ELH-SAG == not measured THEN Diagnosis == '36' No statement (0.9975) RULE 12: IF SER-ELH-SAK == positive (5,=,p) AND SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '3/HB' Immun B THEN (0.9766) Diagnosis == '36' No statement (0.1875) positive (5,=,p) RULE 13: IF SER-ELH-CAK == AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '15/HB' No Infection B (0.1125) THEN Diagnosis == '36' No statement (0.9859) RULE 14: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '1/HB' Infection B (0.8393) Diagnosis == '36' No statement (0.5982) RULE 15: IF SER-ELH-SAK == positive (5,=,p) negative (2,=,n) AND SER-ELH-CAK == AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '15/HB' No Infection B (0.2647)THEN Diagnosis == '27/HB' Successful vaccination B (0.5037)Diagnosis == '29/HB' Vaccination? B (0.9007)

RULE 16: IF SER-ELH-SAK == extremely positive (5,<,g) AND SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '3/HB' Immune B (0.8594) Diagnosis == '26/HB' Possibly Immune B (0.3750) Diagnosis == '36' No statement (0.5313) RULE 17: IF SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '3/HB' Immune B (0.8313) Diagnosis == '26/HB' Possibly Immune B (0.4500) Diagnosis == '36' No statement (0.5500) RULE 18: IF SER-ELH-SAK == not measured AND SER-ELH-SAG == not measured AND SER-ELH-CAK == negative (2,=,n) Diagnosis == '15/HB' No Infection B (0.8125) THEN Diagnosis == '36' No statement (0.6250) RULE 19: ΙF SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAK == extremely positive (5,<,g) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '3/HB' THEN Immune B (0.5982) Diagnosis == '15/HB' No Infection B (0.5179) Diagnosis == '26/HB' Possibly Immune B (0.5179)Diagnosis == '36' No statement (0.6786) RULE 20: ΙF SER-ELH-SAG == not measured AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '15/HB' No inf. B (0.9231) RULE 21: IF SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAK == not measured AND SER-ELH-SAG == not measured THEN Diagnosis == '1/HB' Infection B (0.7188)Diagnosis == '36' No statement (0.7188) RULE 22: IF SER-ELH-SAK == extremely positive (5,<,g) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '29/HB' Vaccination? B THEN (0.8125) Diagnosis == '36' No statement (0.6250)

RULE 23: IF SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAG == not measured AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.8000) RULE 24: IF SER-ELH-CAK == not measured AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '15/HB' No inf. B (0.7188) THEN Diagnosis == '36' No statement (0.7188) RULE 25: IF SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement (0.8000) THEN RULE 26: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.8000) RULE 27: IF SER-ELH-CAK == not measured AND SER-ELH-SAK == not measured AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 28: IF SER-ELH-CAK == not measured AND SER-ELH-SAG == not measured AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '36' No statement (0.6667) THEN RULE 29: IF SER-ELH-SAK == not measured AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '15/HB' No Infection B (0.6667) THEN RULE 30: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-SAK == not measured AND SER-ELH-CAK == negative (2,=,n) Diagnosis == '4/HB' Suspicion B THEN (0.6667)RULE 31: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == not measured AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '4/HB' Suspicion B (0.6667) THEN

RULE 32: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == not measured AND SER-ELH-SAK == not measured THEN Diagnosis == '36' No statement (0.6667) RULE 33: IF SER-ELH-SAG == extremely positive (5,<,g)</pre> AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '36' No statement (0.6667) THEN RULE 34: IF SER-ELH-SAK == positive (5,=,p) AND SER-ELH-SAG == not measured AND SER-ELH-CAK == negative (2,=,n) THEN Diagnosis == '29/HB' Vaccination? B (0.6667) RULE 35: IF SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAG == positive (5,=,p) AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '1/HB' Infection B (0.6667) THEN RULE 36: IF SER-ELH-SAG == extremely positive (5,<,g) AND SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '36' No statement (0.6667) THEN RULE 37: IF SER-ELH-CAK == extremely negative (2,<,g) AND SER-ELH-SAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '3/HB' Immune B (0.6667) RULE 38: IF SER-ELH-SAG == extremely negative (2,<,g) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '6/HB' Not Immune B (0.6667) RULE 39: IF SER-ELH-SAK == extremely negative (2,<,g) AND SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == positive (5,=,p) Diagnosis == '1/HB' Infection B THEN (0.6667)RULE 40: IF SER-ELH-HCK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9989) SER-ELH-HCK == not measured RULE 41: IF THEN Diagnosis == '36' No statement (0.9989)

RULE 42: IF SER-ELH-HCK == positive (5,=,p) Diagnosis == '1/HCV' Infection C (0.9942) THEN RULE 43: IF SER-ELH-HCK == extremely negative (2,<,g) THEN Diagnosis == '36' No statement (0.8000) RULE 44: IF SER-ELH-HCK == extremely positive (5,<,g) Diagnosis == '4/HCV' Suspicion C THEN (0.8000)RULE 45: IF SER-ELH-AAK == positive (5,=,p) AND SER-ELH-AGM == negative (2,=,n) Diagnosis == '36' No statement (0.9988) THEN RULE 46: IF SER-ELH-AAK == not measured AND SER-ELH-AGM == not measured THEN Diagnosis == '36' No statement (0.9982) RULE 47: IF SER-ELH-AAK == negative (2,=,n) AND SER-ELH-AGM == negative (2,=,n) Diagnosis == '36' No statement (0.9980) THEN SER-ELH-AAK == negative (2,=,n) RULE 48: IF AND SER-ELH-AGM == not measured Diagnosis == '36' No statement (0.9630) THEN SER-ELH-AGM == positive (5,=,p) RULE 49: IF AND SER-ELH-AAK == positive (5,=,p) THEN Diagnosis == '36' No statement (0.9524) RULE 50: IF SER-ELH-AGM == not measured AND SER-ELH-AAK == positive (5,=,p) THEN Diagnosis == '36' No statement (0.8333) Diagnosis == '10/AGM' Test AGM (0.3333) RULE 51: IF SER-ELH-AAK == extremely positive (5,<,g)</pre> AND SER-ELH-AGM == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9333) RULE 52: IF SER-ELH-AAK == not measured AND SER-ELH-AGM == negative (2,=,n) Diagnosis == '36' No statement (0.8000) THEN SER-ELH-AGM == extremely positive (5,<,g)</pre> RULE 53: IF AND SER-ELH-AAK == positive (5,=,p) THEN Diagnosis == '36' No statement (0.6667)

RULE 54: IF SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9982) Diagnosis == '21/HB' Test 4 We B (0.0202) RULE 55: IF SER-ELH-CAK == not measured AND SER-ELH-SAK == not measured AND SER-ELH-SAG == not measured Diagnosis == '36' No statement (0.9945) THEN Diagnosis == '10/HB' Test B (0.0302) RULE 56: IF SER-ELH-SAK == positive (5,=,p) AND SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9897) RULE 57: IF SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement (0.5773) THEN Diagnosis == '10/CGM' Test CGM (0.8773) SER-ELH-SAG == positive (5,=,p) RULE 58: IF AND SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '36' No statement (0.4286) THEN Diagnosis == '8/BVE' Test 2 We BVE (0.9026) Diagnosis == '22/SAG' Test 2 Mo SAG (0.2143) Diagnosis == '22/BVE' Test 2 Mo BVE (0.4286) RULE 59: IF SER-ELH-SAK == positive (5,=,p) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement (0.9714) THEN RULE 60: IF SER-ELH-SAK == extremely positive (5,<,g) AND SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9600) RULE 61: IF SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement (0.9524) THEN

RULE 62: IF SER-ELH-SAK == not measured AND SER-ELH-SAG == not measured AND SER-ELH-CAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9474) SER-ELH-CAK == extremely positive (5,<,g)</pre> RULE 63: IF AND SER-ELH-SAK == extremely positive (5,<,g) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement (0.9333) THEN RULE 64: IF SER-ELH-SAG == not measured AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.9231) RULE 65: IF SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAK == not measured AND SER-ELH-SAG == not measured THEN Diagnosis == '36' No statement (0.5909) (0.7273) Diagnosis == '10/SAK' Test SAK Diagnosis == '8/BVE' Test 2 We BVE (0.5909) RULE 66: IF SER-ELH-SAK == extremely positive (5,<,g) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement (0.8571) THEN RULE 67: IF SER-ELH-CAK == positive (5,=,p) AND SER-ELH-SAG == not measured AND SER-ELH-SAK == negative (2,=,n) Diagnosis == '10/SAG' Test SAG (0.8000) THEN RULE 68: IF SER-ELH-CAK == not measured AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '36' No statement THEN (0.7273) Diagnosis == '10/CAK' Test CAK (0.7273) IF SER-ELH-CAK == extremely positive (5,<,g) RULE 69: AND SER-ELH-SAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) Diagnosis == '10/CGM' Test CGM (0.8000) THEN

RULE 70: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.8000) RULE 71: IF SER-ELH-CAK == not measured AND SER-ELH-SAK == not measured AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 72: IF SER-ELH-CAK == not measured AND SER-ELH-SAG == not measured AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 73: IF SER-ELH-SAK == not measured AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 74: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-SAK == not measured AND SER-ELH-CAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 75: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == not measured AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '10/BVE' Test BVE (0.6667) RULE 76: IF SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == not measured AND SER-ELH-SAK == not measured THEN Diagnosis == '10/BVE' Test BVE (0.6667) RULE 77: IF SER-ELH-SAG == extremely positive (5,<,g) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 78: IF SER-ELH-SAK == positive (5,=,p) AND SER-ELH-SAG == not measured AND SER-ELH-CAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667)

RULE 79: IF SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAG == positive (5,=,p) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '8/BVE' Test 2 We BVE (0.6667) RULE 80: IF SER-ELH-SAG == extremely positive (5,<,g) AND SER-ELH-CAK == extremely positive (5,<,g) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '10/CGM' Test CGM (0.6667) RULE 81: IF SER-ELH-CAK == extremely negative (2,<,g) AND SER-ELH-SAK == positive (5,=,p) AND SER-ELH-SAG == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 82: IF SER-ELH-SAG == extremely negative (2,<,g) AND SER-ELH-CAK == negative (2,=,n) AND SER-ELH-SAK == negative (2,=,n) THEN Diagnosis == '36' No statement (0.6667) RULE 83: IF SER-ELH-SAK == extremely negative (2,<,g) AND SER-ELH-SAG == positive (5,=,p) AND SER-ELH-CAK == positive (5,=,p) THEN Diagnosis == '8/BVE' Test 2 We BVE (0.6667) RULE 84: IF SER-ELH-HCK == negative (2,=,n) Diagnosis == '36' No statement (0.0725) THEN Diagnosis == '10/HCV' Test HCV (0.0171) Diagnosis == '22/HCV' Test 2 Mo HCV (0.9701) RULE 85: IF SER-ELH-HCK == not measured Diagnosis == '36' No statement (0.4807) THEN Diagnosis == '10/HCV' Test HCV (0.8337) Diagnosis == '22/HCV' Test 2 Mo HCV (0.0181) RULE 86: IF SER-ELH-HCK == positive (5,=,p) Diagnosis == '36' No statement THEN (0.9942) RULE 87: IF SER-ELH-HCK == extremely negative (2,<,g) Diagnosis == '10/HCV' Test HCV (0.6667) THEN Diagnosis == '22/HCV' Test 2 Mo HCV (0.6667) RULE 88: IF SER-ELH-HCK == extremely positive (5,<,g) Diagnosis == '36' No statement (0.8000) THEN