

Horn Minimization

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Introduction



- ► Correlation relations (*implications*).
 - e.g: movies and genres, cyber-punk --> sci-fi
- ▶ Minimization without loss of knowledge.
 - e.g: sci- $fi \longrightarrow sci$ -fi is useless
- Study of existing algorithms.



Outline



I - Horn theories

Closure and implications Minimization task

II - Some Algorithms

Minimizing the input Building the result

III - Experiments

Experiments



Closure operator and systems

1.1 - Closure and implications



Set Σ of attributes. A map $\varphi: 2^{\Sigma} \longrightarrow 2^{\Sigma}$ is a *closure operator* if, $\forall X, Y \subseteq \Sigma$:

- $ightharpoonup X \subseteq \varphi(X)$ (extensive)
- $\triangleright \varphi(\varphi(X)) = \varphi(X)$ (idempotent)

Associated terminology:

- ightharpoonup X is *closed* if $X = \varphi(X)$,
- \triangleright Σ^{φ} set of closed sets: *closure system*,
- \triangleright Σ^{φ} is closed under *intersection*, contains Σ.



Implications

1.1 - Closure and implications



 $A, B \subseteq \Sigma$. An *implication* is:

- $ightharpoonup A \longrightarrow B$, A premise, B conclusion,
- ▶ $M \subseteq \Sigma$ *model* of $A \longrightarrow B$:
 - $\triangleright \ \ B \subseteq M \lor A \nsubseteq M, \quad (\simeq B \lor \neg A)$
 - \triangleright $M \models A \longrightarrow B$.

Set of implications \mathcal{L} : *implication system*.

 \triangleright $\mathcal{L} \models A \longrightarrow B$: all models of \mathcal{L} are models of $A \longrightarrow B$,



Implications and closure

1.1 - Closure and implications



${\cal L}$ an implication system:

ightharpoonup models of \mathcal{L} form a *closure system*:

$$\Sigma^{\mathcal{L}} = \{ M \subseteq \Sigma \mid M = \mathcal{L}(M) \}$$

▶ closure operator $\mathcal{L}(X)$: smallest model (inclusion wise) of \mathcal{L} containing $X, X \subseteq \Sigma$:

$$\mathcal{L}(X) = \bigcap \{ M \in \Sigma^{\mathcal{L}} \mid X \subseteq M \}$$

 $\blacktriangleright \ \mathcal{L} \models A \longrightarrow B \text{ iff } B \subseteq \mathcal{L}(A).$



Redundancy, equivalence, minimality

1.2 - Minimization task



${\cal L}$ and ${\cal L}'$ implication systems:

- ▶ $A \longrightarrow B \in \mathcal{L}$ redundant if $\mathcal{L} \{A \longrightarrow B\} \models A \longrightarrow B$,
- $\triangleright \mathcal{L}' \models \mathcal{L}$: all implications of \mathcal{L} follow from \mathcal{L}' ,
- $\triangleright \mathcal{L}' \models \mathcal{L}$ and $\mathcal{L} \models \mathcal{L}'$: equivalent systems.
- \triangleright \mathcal{L} *minimum* if no possible \mathcal{L}' such that:
 - $\triangleright \mathcal{L}'$ equivalent to \mathcal{L} ,
 - $\triangleright \mathcal{L}'$ has fewer implications than \mathcal{L} .

Recall property:
$$(\mathcal{L}^- := \mathcal{L} - \{A \longrightarrow B\})$$

 $\blacktriangleright \mathcal{L}^- \models A \longrightarrow B \text{ iff } B \subseteq \mathcal{L}^-(A).$



Canonical basis

1.2 - Minimization task



Particular sets:

- ▶ $P \subseteq \Sigma$ *pseudo-closed* in \mathcal{L} if:
 - $\triangleright P \neq \mathcal{L}(P)$,
 - \triangleright if $Q \subset P$ and Q pseudo-closed, then $\mathcal{L}(Q) \subseteq P$.
- ▶ $Q \subseteq \Sigma$ quasi-closed in \mathcal{L} if:
 - $\forall P \subseteq Q, \mathcal{L}(P) \subseteq Q \text{ or } \mathcal{L}(P) = \mathcal{L}(Q),$
- ▶ pseudo-closed → quasi-closed.

Duquenne-Guigues (canonical) base:

$$\{P \longrightarrow \mathcal{L}(P) \mid P \text{ pseudo-closed }\}$$



Small Example 1.2 - Minimization task



Let \mathcal{L} be an implication system:

- $\Sigma = \{a, b, c, d, e, f\},\$
- $\blacktriangleright \ \mathcal{L} = \{ab \longrightarrow cde, cd \longrightarrow f, c \longrightarrow a, d \longrightarrow b, abcd \longrightarrow ef\}.$

We have:

- \triangleright $\mathcal{L}(b) = b$, b is closed, hence a model of \mathcal{L} ,
- \triangleright $\mathcal{L}(ab) = abcdef$, ab is not a model, (abcdef is)
- ightharpoonup abcd \longrightarrow ef is redundant,



Algorithms Core

2.1 - Minimizing the input



Two main ideas:

- minimizing input system
 - ▶ algorithms from FCA and databases,
- building a minimum system against the input
 - query learning interpretation,

Some notations, given \mathcal{L} :

- $ightharpoonup |\mathcal{B}|$ number of implications, $|\Sigma|$ number of attributes,
- $\triangleright |\mathcal{L}| = O(|\mathcal{B}||\Sigma|)$, size of \mathcal{L} .



First algorithm

2.1 - Minimizing the input



MINCOVER:

- ▶ from Day, Wild, (80's),
- two steps:
 - 1. maximize the conclusion $A \longrightarrow B$ becomes $A \longrightarrow \mathcal{L}(A)$
 - 2. remove redundant information if $\mathcal{L}(A) = \mathcal{L}^{-}(A)$, $A \longrightarrow \mathcal{L}(A)$ is redundant
- ▶ output: *canonical* base, complexity: $O(|\mathcal{B}||\mathcal{L}|)$.

Recall:
$$\mathcal{L}^- = \mathcal{L} - \{A \longrightarrow \mathcal{L}(A)\}$$



A variation

2.1 - Minimizing the input



DuquenneMin:

- ▶ variation of MINCOVER by Duquenne (2007),
- three steps:
 - 1. quasi-closure and redundancy elimination if $B \subseteq \mathcal{L}^-(A)$, $A \longrightarrow B$ is useless else $A \longrightarrow B$ becomes $\mathcal{L}^-(A) \longrightarrow (\mathcal{L}^-(A) \cup B)$
 - 2. sort implications in ⊆-compatible order (premises)
 - 3. *iteratively build* Duquenne-Guigues base if $\mathcal{L}^-(A)$ *pseudo-closed*, add $\mathcal{L}^-(A) \longrightarrow \mathcal{L}(A)$ to the result
- ▶ output: *canonical* base, complexity: $O(|\mathcal{B}||\mathcal{L}|)$.



Database approach

2.1 - Minimizing the input



MAIERMIN:

- ▶ functional dependency based algorithm, Maier (80's),
- steps:
 - 1. redundancy elimination if $B \subseteq \mathcal{L}^-(A)$, $A \longrightarrow B$ is useless
 - equivalence classes reduction group implications by premises closure reduce those classes
- ▶ output: minimum basis, complexity: $O(|\mathcal{B}||\mathcal{L}|)$.



General principle

2.2 - Building the result



Query learning and Angluin algorithm (90's):

- ▶ aim: learn a theory by constructing an hypothesis
- oracle answering queries (questions)
- queries:
 - ▷ equivalence: is our hypothesis equivalent to the target?
 - ▶ membership: is a set a model of the target?
- ▶ improve by *counterexample*
 - positive: model of the target, not of the hypothesis
 - ▷ negative: model of the hypothesis, not of the target

AFP-Based Algorithm

2.2 - Building the result



AFP-Based:

- derived from Angluin, no proof yet,
- principle:
 - 1. take implications one by one,
 - 2. refine the hypothesis:
 - use premises to generate possible counter-examples add right-closed implications or refine old ones
- expected output: canonical base,
- idea of complexity: $O(|\mathcal{B}|^3|\mathcal{L}|)$.



Using minimality constraint

2.2 - Building the result



BercziMin:

- ▶ logic based, Berczi, 2017
- principle:
 - 1. build a basis \mathcal{L}_c against the input \mathcal{L}
 - 2. repeat minimality selection up to equivalence
 - 3. minimality selection: select the next minimal negative counter-example A, add $A \longrightarrow \mathcal{L}(A)$ to $\mathcal{L}_{\mathcal{L}}$
- ▶ output: *canonical* base, complexity: $O(|\mathcal{B}|^2|\mathcal{L}|)$.



Context 1

3.1 - Experiments



Practical aspect:

- context of FCA, previous study of closure operators,
- use datasets from UCI repository (scaling):

 - ▶ SPECT: 23 attributes,
- ightharpoonup use of CLOSURE (\simeq forward chaining)
- ► C++, boost, python.

Context 2

3.1 - Experiments



1 dataset give rise to 5 systems:

- ▶ Duquenne-Guigues basis (DG),
- minimal generators (mingen, right-closed),
- proper implications (proper)
- ▶ Maier minimum on mingen (min 1, right-closed),
- ▶ Maier minimum on proper (*min 2*)

	\mathcal{L}	Σ	$ \mathcal{B} $
	minimum		3382
Flare	mingen	49	39787
	proper		10692
SPECT	minimum		2169
	mingen	23	44341
	proper		8358

Table: Summary of real datasets characteristics



Overhaul results

3.1 - Experiments



\mathcal{L}		MinCov	Duq	Maier	Berczi	AFP
Flare	DG	0.097	0.117	0.211	27.922	96.178
	min 1	0.134	0.194	0.288	27.750	98.145
	min 2	0.200	0.190	0.308	30.063	111.944
	proper	1.684	0.933	0.917	88.375	402.453
	mingen	16.047	7.981	7.576	160.328	2514.610
SPECT	DG	0.045	0.066	0.108	10.328	22.454
	min 1	0.061	0.080	0.134	8.156	19.438
	min 2	0.078	0.070	0.150	8.250	26.980
	proper	0.930	0.394	0.451	51.063	114.564
	mingen	24.077	10.206	10.858	194.875	863.903

Table: Comparison of the algorithms on real datasets (execution in s)



Observation

3.1 - Experiments



Observations on these data:

- ► cost of AFP and BERCZIMIN.
- DuquenneMin, MaierMin efficient on non-minimum cases,
- ► MINCOVER slightly better on right-closed minimum cases.

Generating random implication (given $|\Sigma|$, $|\mathcal{B}|$):

- discrete uniform distribution on size, elements,
- ▶ premise A, conclusion B, yield $A B \longrightarrow B$.



Minimum tests 1

3.1 - Experiments



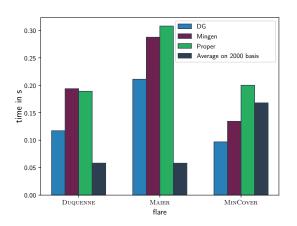


Figure: Flare - Random against and minimum basis: 49 attr, 3382 imp

Minimum tests 2

3.1 - Experiments



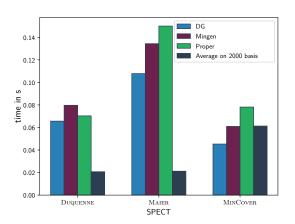
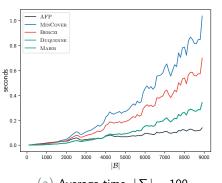


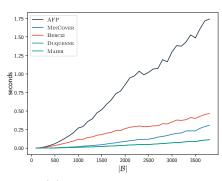
Figure: SPECT - Random against minimum basis: 23 attr, 2169 imp

Insight on random tests

3.1 - Experiments







(a) Average time, $|\Sigma| = 100$

(b) Average time, $|\Sigma| = 500$

Figure: Random generated tests for fixed $|\Sigma|$ (over 500 ex)



Observations:

- ▶ times of MAIERMIN, DUQUENNEMIN on redundant cases,
- first glance at random: efficiency of AFP.

Explanations:

- redundancy elimination as first step,
- suggests a study of underlying structure (AFP).

Boundaries:

- valid in our context,
- random generation,
- suggests extension of tests.





Conclusion

Purpose:

study of minimization algorithms.

Results:

- algorithms from various communities,
- ▶ in practice: redundancy elimination

Perspectives:

- theoretical study of systems structure, AFP proof and complexity,
- experimental aspect, extend tests.

