Inductive Logic Programming

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Outline

1. Predictive ILP
   - Learning from entailment
     - Bottom-up systems
     - Top-down systems
   - Learning from interpretations
2. Descriptive ILP

Predictive ILP

- Aim:
  - classifying instances of the domain, i.e.
  - predicting the class
- Two settings:
  - Learning from entailment
  - Learning from interpretations

Learning from Entailment

- Given
  - A set of positive example E^+
  - A set of negative examples E^-
  - A background knowledge B
  - A space of possible programs $\mathcal{H}$
- Find a program $P \in \mathcal{H}$ such that
  - $\forall e^+ \in E^+, P \cup B \models e^+$ (completeness)
  - $\forall e^- \in E^-, P \cup B \not\models e^-$ (consistency)

Targeted Mailing

customer

Name	Age	Sex	Address	Resp
john	35	m	ca	no
mary	25	f	ca	no
ann	29	f	wa	yes
steve	31	m	va	no

article

Name	Category	Size	Price
bike_1	sport	l	1000
jacket_2	clothing	l	150
tent_2	outdoor	m	250

transaction

Name	Article	Quantity
john	bike_1	2
ann	jacket_2	1
steve	bike_1	1
john	tent_2	1
ann	bike_1	3

Mailing Example

- Positive examples $E^+ = \{respond(ann)\}$
- Negative examples
  $E^- = \{respond(john), respond(mary), respond(steve)\}$
- Background B = facts for relations *customer*, *transaction* and *article*
  $customer(john, 35, m, ca).$
  $customer(mary, 25, f, ca).$
  $customer(ann, 29, f, wa)....$
  $transaction(john, bike\_1, 2).$
  $transaction(ann, jacket\_2, 1)....$
  $article(bike\_1, sport, l, 1000).$
  $article(jacket\_2, clothing, l, 150)....$

Mailing Example

- Space of programs $\mathcal{H}$: programs containing clauses with
  - in the head $respond(Customer)$
  - in the body a conjunction of literals from the set
    $\{customer(Customer, Age, Sex, Address),$
    $transaction(Customer, Article, Quantity),$
    $article(Article, Category, Price),$
    $Age = constant, Sex = constant, \ldots\}$
- Possible solution
  $respond(Customer) \leftarrow transaction(Customer, Article, \_Quantity),$
  $article(Article, Category, \_Size, \_Price),$
  $Category = clothing$

Definitions

- $covers(P, e) = true$ if $B \cup P \models e$
- $covers(P, E) = \{e \in E | covers(P, e) = true\}$
- A theory P is more general than Q if $covers(P, U) \supseteq covers(Q, U)$
- If $B \cup P \models Q$ then $B \cup Q \models e \Rightarrow B \cup P \models e$ so P is more general than Q
- A clause C is more general than D if $covers(\{C\}, U) \supseteq covers(\{D\}, U)$
- If $B, C \models D$ then C is more general than D
- If a clause covers an example, all of its generalizations will (*covers* is antimonotonic)
- If a clause does not cover an example, none of its specializations will

Theta Subsumption

- A clause
  $h \leftarrow b_1, \dots, b_n$
  can be seen as a set of literals $\{h, not\ b_1, \dots, not\ b_n\}$
- A substitution θ is a replacement of variable with terms:
  $\theta = \{X/a, Y/b\}$
- C θ-subsumes D ($C \geq D$) if there exists a substitution θ such that $C\theta \subseteq D$ [Plotkin 70]
- $C \geq D \Rightarrow C \models D \Rightarrow B, C \models D \Rightarrow C$ is more general than D
- $C \models D \not\Rightarrow C \geq D$

Examples of Theta Subsumption

- $C1 = father(X, Y) \leftarrow parent(X, Y)$
- $C2 = father(X, Y) \leftarrow parent(X, Y), male(X)$
- $C3 = father(john, steve) \leftarrow parent(john, steve), male(john)$
- $C1 = \{father(X, Y), not\ parent(X, Y)\}$
- $C2 = \{father(X, Y), notparent(X, Y), not\ male(X)\}$
- $C3 = \{father(john, steve), not\ parent(john, steve), not\ male(john)\}$
- $C1 \geq C2$ with $\theta = \emptyset$
- $C1 \geq C3$ with $\theta = \{X/john, Y/steve\}$
- $C2 \geq C3$ with $\theta = \{X/john, Y/steve\}$

Example of $C \models D \not\Rightarrow C \geq D$

- $C = even(X) \leftarrow even(half(X)).$
- $D = even(X) \leftarrow even(half(half(X))).$
- $C \models D$: we can obtain D by resolving C with itself, but
- $C \not\geq D$: there is no substitution θ such that $C\theta \subseteq D$

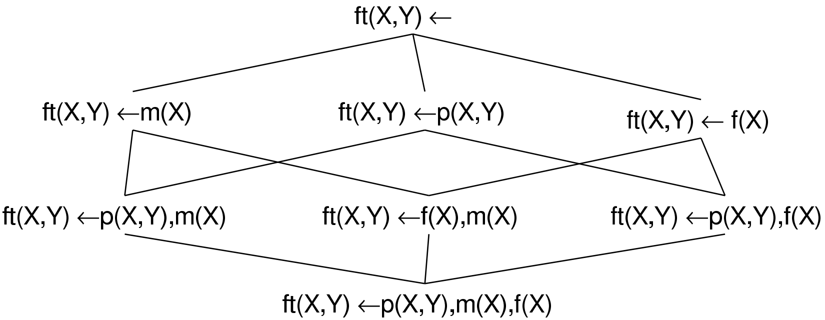
In Practice

- Coverage test: SLD or SLDNF resolution
  - Try to derive e from $B \cup P \cup \{C\}$
- Generality order:
  - θ-subsumption

Properties of Theta Subsumption

- θ-subsumption induces a lattice in the space of clauses
- Every set of clauses has a least upper bound (lub) and a greatest lower bound (glb)
- This is not true for the generality relation based on logical consequence

Lattice


ft(X,Y) ←
ft(X,Y) ←m(X)
ft(X,Y) ←p(X,Y)
ft(X,Y) ← f(X)
ft(X,Y) ←p(X,Y),m(X)
ft(X,Y) ←f(X),m(X)
ft(X,Y) ←p(X,Y),f(X)
ft(X,Y) ←p(X,Y),m(X),f(X)

Least General Generalization

- $lgg(C, D) =$ least upper bound in the θ-subsumption order
- An algorithm exists which has complexity $O(s^2)$ where s is the size of the clauses
- Example:

$$C = father(john, mary) \leftarrow parent(john, mary), male(john)$$
$$D = father(david, steve) \leftarrow parent(david, steve), male(david)$$
$$lgg(C, D) = father(X, Y) \leftarrow parent(X, Y), male(X)$$

- For a set of n clauses the complexity is $O(s^n)$

Least General Generalization Algorithm

- The algorithm keeps a set of anti-substituons A that contains elements of the form $V/t1, t2$ meaning that variable V replaced the term $t1$ in the first formula and the term $t2$ in the second formula
- The *lgg* of two terms $f1(s1, \ldots, sn)$ and $f2(t1, \ldots, tm)$ is:

$$f1(lgg(s1, t1), \ldots, lgg(sn, tn))$$

  if $f1/n = f2/m$, otherwise
  - if an element of the form $V/f1(s1, \ldots, sn), f2(t1, \ldots, tm)$ is present in A, then the *lgg* is V
  - otherwise let V be a new variable, add $V/f1(s1, \ldots, sn), f2(t1, \ldots, tm)$ to A and the *lgg* is V

Least General Generalization Algorithm

- Examples

$lgg(f(a,b,c), f(a,c,d)) = f(lgg(a,a), lgg(b,c), lgg(c,d)) = f(a,X,Y)$,
$A = \{X/b,c, Y/c,d\}$
$lgg(f(a,a), f(b,b)) = f(lgg(a,b), lgg(a,b)) = f(X,X)$, $A = \{X/a,b\}$

- Note that the same variable X is used in both arguments of the second example because it indicates the *lgg* of the same two terms

$lgg(f(a,b), f(b,a)) = f(lgg(a,b), lgg(b,a)) = f(X,Y)$,
$A = \{X/a,b, Y/b,a\}$

- Note that two different variables X and Y are used because the order of the terms is different

Least General Generalization Algorithm

- The *lgg* of two literals $L1 = (not)p(s1, ..., sn)$ and $L2 = (not)q(t1, ..., tm)$ is
  - undefined if $L1$ and $L2$ do not have the same sign or if $p/n \neq q/m$, otherwise

$$lgg(L1, L2) = (not)p(lgg(s1, t1), ...lgg(sn, tn))$$

- Examples:
  - $lgg(parent(john, mary), parent(john, steve)) = parent(john, X)$ $A = \{X/mary, steve\}$
  - $lgg(parent(john, mary), not\ parent(john, steve)) = undefined$
  - $lgg(parent(john, mary), father(john, steve)) = undefined$

Least General Generalization Algorithm

- $lgg(C, D) = \{lgg(L, K) | L \in C, K \in D$ and $lgg(L, K)$ is defined$\}$
- Examples

$C = father(john, mary) \leftarrow parent(john, mary), male(john)$
$D = father(david, steve) \leftarrow parent(david, steve), male(david)$
$lgg(C, D) = father(X, Y) \leftarrow parent(X, Y), male(X),$
$A = \{X/john, david, Y/mary, steve\}$

$C = win(conf1) \leftarrow occ(place1, x, conf1), occ(place2, o, conf1)$
$D = win(conf2) \leftarrow occ(place1, x, conf2), occ(place2, x, conf2)$
$lgg(C, D) = win(Conf) \leftarrow occ(place1, x, Conf), occ(L, x, Conf),$
$occ(M, Y, Conf), occ(place2, Y, Conf)$
$A = \{Conf/conf1, conf2, L/place1, place2, M/place2, place1, Y/o, x\}$

Relative Subsumption

- θ subsumption does not take into account background knowledge
- $C \geq D \Leftrightarrow \models \forall (C\theta \rightarrow D)$
- Relative Subsumption [Plotkin 71]: C θ subsume D relative to background B ($C \geq_B D$) if there exists a substitution θ such that $B \models \forall (C\theta \rightarrow D)$

Relative Least General Generalization

- Relative Least General Generalization (rlgg): lgg with respect to relative subsumption.
- It does not exists in the general case of B a set of Horn clauses
- It exists in the case that B is a set of ground atoms and can be computed in this way:
- $rlgg((H1 \leftarrow B1),(H2 \leftarrow B2)) =$
  $lgg((H1 \leftarrow B1, B),(H2 \leftarrow B2, B))$

Relative Least General Generalization

- Example

$C1 = father(john, mary)$

$C2 = father(david, steve)$

$B = \{parent(john, mary), parent(david, steve),$
$parent(kathy, mary), female(kathy),$
$male(john), male(david)\}$

Relative Least General Generalization

- Example

$C1 \leftarrow B = fa(j, m) \leftarrow p(j, m), p(d, s), p(k, m), f(k), m(j), m(d)$

$C2 \leftarrow B = fa(d, s) \leftarrow p(j, m), p(d, s), p(k, m), f(k), m(j), m(d)$

$rlgg(C1, C2) = fa(X, Y) \leftarrow p(j, m), p(X, Y), p(Z, m),$
$p(W, U), p(d, s), p(S, U), p(T, m), p(R, Y), p(k, m),$
$f(k), m(j), m(X), m(W), m(d)$

$A = \{X/j, d, Y/m, s, Z/j, k, W/d, j, U/s, m, S/d, k, T/k, j, R/k, d\}$

Reduced clause

- Two clauses C and D are equivalent (relative to B) if $C \geq D$ and $D \geq C$ ($C \geq_B D$ and $D \geq_B C$)
- A clause C is reduced (relative to B) if it does not contain any subset D that is equivalent to C (relative to B)
- $C = rlgg(C1, C2) = fa(X, Y) \leftarrow p(j, m), p(X, Y), p(Z, m),$
  $p(W, U), p(d, s), p(S, U), p(T, m), p(R, Y), p(k, m),$
  $f(k), m(j), m(X), m(W), m(d)$
  is equivalent to
  $D = fa(X, Y) \leftarrow p(j, m), p(X, Y), p(d, s), p(k, m),$
  $f(k), m(j), m(X), m(d)$
  and is equivalent relative to B to
  $D = fa(X, Y) \leftarrow p(X, Y), m(X)$

Bottom-up Systems

- Covering loop
- Search for a clause from specific to general

Learn(E, B)
$P := 0$
repeat /* covering loop */
    $C :=$GenerateClauseBottomUp(E, B)
    $P := P \cup \{C\}$
    Remove from E the positive examples covered by P
until Sufficiency criterion
return P

Golem [Muggleton, Feng 90]

- Bottom-up system
- Generalization by means of rlgg
- Sufficiency criterion: $E^+ = \emptyset$

Golem

GolemGenerateClause(E, B)
select randomly some couples of examples from E^+
compute their rlgg
let C be the rlgg that covers most positive examples
    while covering no negative
repeat
    randomly select some examples from E^+
    compute the rlgg between C and each selected example
    let C be the rlgg that covers most positive examples
        while covering no negative
    remove from E^+ the examples covered by C
while C covers no negatives
remove literals from the body of C until C covers
    some negative examples
return C

Top-down Systems

- Covering loop as bottom-up systems
- Search for a clause from general to specific using beam search
- Score clauses using a heuristic function

Top-down Systems

GenerateClauseTopDown(E,B)
Beam $:= \{p(X) \leftarrow true\}$
BestClause $:= null$
repeat /* specialization loop */
    Remove the first clause *C* of *Beam*
    compute $\rho(C)$
    score all the refinements
    update *BestClause*
    add all the refinements to the beam
    order the beam according to the score
    remove the last clauses that exceed the dimension *d*
until the Necessity criterion is satisfied
return *BestClause*

Typical Stopping Criteria

- Sufficiency criteria:
  - $E^{+} = \emptyset$
  - GenerateClauseTopDown returns *null*
  - a disjunction of the above
- Necessity criteria
  - the number of negative examples covered by *BestClause* is 0
  - the number of negative examples covered by *BestClause* is below a threshold
  - *Beam* is empty
  - a disjunction of the above

Refinement Operator

- $\rho(C) = \{D | D \in L, C \geq D\}$
- where L is the space of possible clauses
- A refinement operator usually generates only minimal specializations
- A typical refinement operator applies two syntactic operations to a clause
  - it applies a substitution to the clause
  - it adds a literal to the body

Heuristic Functions

- n^+, n^- number of positive and negative examples in the training set, $n = n^+ + n^-$
- $n^+(C), n^-(C)$ number of positive and negative examples covered by clause C
- $n(C) = n^+(C) + n^-(C)$
- Accuracy: $Acc = P(+|C)$ (more accurately Precision), $P(+|C)$ can be estimated by
  - relative frequency: $P(+|C) = \frac{n^+(C)}{n(C)}$
  - m-estimate: $P(+|C) = \frac{n^+(C)+mP(+)}{n(C)+m}$, where $P(+) = n^+/n$
  - Laplace: m-estimate with $m = 2, P(+) = 0.5$ $P(+|C) = \frac{n^+(C)+1}{n(C)+2}$

Heuristic Functions

- Coverage: $Cov = n^+(C) - n^-(C)$
- Informativity: $Inf = \log_2(Acc)$
- Weighted relative accuracy: $WRAcc = P(C)(P(+|C) - P(+))$

FOIL [Quinlan 90]

- Top-down system with
  - Dimension of the beam: 1
  - Heuristic: (approximately) weighted gain of *Inf*:
    $H = n(C')(\mathit{Inf}(C') - \mathit{Inf}(C))$
  - Refinement operator: addition of a literal or unification
  - Sufficiency criterion: $E^+ = \emptyset$
  - Necessity criterion: $n^-(\mathit{BestClause}) = 0$

Progol [Muggleton 95]

- Top-down system with
  - Dimension of the beam: user defined
  - Heuristic: Compression: $Comp = n^+(C) - n^-(C) - |C|$
  - Refinement operator: adds a literal from the most specific clause $\bot$ after having replaced some of the constants with variables
  - Sufficiency criterion: $E^+ = \emptyset$
  - Necessity criterion: $Beam = \emptyset$ or a maximum number of iterations of the loop is reached

Learning from Interpretations

- Interpretation = set of ground atoms.
- Aim: learning a classifier for logical interpretations
- Classifier: a set of disjunctive clauses
- Disjunctive clause
  $C = h_1 \vee h_2 \vee \ldots \vee h_n \leftarrow b_1, b_2, \ldots, b_m$
  can be seen as a set of literals
  $\{h_1, \ldots, h_n, not\ b_1, \ldots, not\ b_m\}$
- $head(C) = h_1 \vee h_2 \vee \ldots \vee h_n$ or $\{h_1, \ldots, h_n\}$
- $body(C) = b_1, b_2, \ldots, b_m$ or $\{b_1, \ldots, b_m\}$
- $body^+(C) =$ set of positive literals of $body(C)$
- $body^-(C) =$ set of atoms of negative literals of $body(C)$

Learning from Interpretations

- Set of clauses as a classifier
  - an interpretation is positive if all the clauses are true in the interpretation
  - an interpretation is negative if there exists at least one clause that is false in it
- A clause C is true in an interpretation I if for all grounding substitutions θ of C:
  $I \models body(C)\theta \rightarrow head(C)\theta \cap I \neq \emptyset$
  or
  $body^{+}(C)\theta \subseteq I \wedge body^{-}(C)\theta \cap I = \emptyset \rightarrow head(C)\theta \cap I \neq \emptyset$

Test of the Truth of a Clause

- Range restricted clause: all the variables of the clause appear in positive literals in the body
- Range restricted clause C, finite interpretation I: run the query $?-body(C), not\ head(C)$ against a logic program containing I
- If $C = h_1 \vee h_2 \vee \ldots \vee h_n \leftarrow b_1, b_2, \ldots, b_m$ then the query is $?-b_1, b_2, \ldots, b_m, not\ h_1, not\ h_2, \ldots, not\ h_n$
- If the query succeeds, C is false in I. If the query fails, C is true in I [De Raedt, Bruynooghe 93]

Example

- $I = \{female(liz), male(richard),$
  $gorilla(liz), gorilla(richard)\}$
- $C = male(X) \vee female(X) \leftarrow gorilla(X)$: the clause is true in I because the query $?-gorilla(X), not\ male(X), not\ female(X)$ fails
- $C = male(X) \leftarrow gorilla(X)$: the clause is false in I because the query
  $?-gorilla(X), not\ male(X)$ succeeds with $\theta = \{X/liz\}$.

Learning from Interpretations

- **Given**
  - a space of possible clausal theories $\mathcal{H}$
  - a set P of interpretations
  - a set N of interpretations
- **Find**: a clausal theory $H \in \mathcal{H}$ such that
  - for all $p \in P$, $p \models H$
  - for all $n \in N$, $n \not\models H$
- Less expressive than learning from entailment: no recursive definitions

Test with Background

- Background: a normal program B
- Truth of a clause C in the interpretation $M(B \cup I)$ where M is the model according to the chosen semantics and I is an interpretation (i.e. $B \cup I \models C$)
- Range restricted clause C, normal program B containing only range restricted clauses, interpretation I: run the query $? - body(C), not\ head(C)$ against the logic program $B \cup I$.
- If the query succeeds, C is false in $M(B \cup I)$ ($B \cup I \not\models C$). If the query fails, C is true in $M(B \cup I)$ ($B \cup I \models C$)

Learning from Int. with Background

Given

- a space of possible clausal theories $\mathcal{H}$
- a set P of interpretations
- a set N of interpretations
- a background theory B

Find: a clausal theory $H \in \mathcal{H}$ such that

- for all $p \in P$, $B \cup p \models H$
- for all $n \in N$, $B \cup n \not\models H$

Generality Relation

- $cover(\{C\}, e) = true$ if $e \models C$
- $C \geq D \Rightarrow C \models D \Rightarrow D$ is more general than C
- the relation is reversed
- Example:

$false \leftarrow true$
$false \leftarrow gorilla(X)$
$female(X) \leftarrow gorilla(X)$
$female(X) \vee male(X) \leftarrow gorilla(X)$

ICL [De Raedt, Van Laer, 95]

- Dual version of a top down entailment algorithm:
  - coverage loop is performed on negative examples
- Updates CN2 to first order

ICL(P, N, B)
$H := \emptyset$
repeat
    C :=FindBestClause(P, N, B)
    if $C \neq null$ then
        add C to H
        remove from N all interpretations that are false for C
until $C = null$ or N is empty
return H

ICL FindBestClause

FindBestClause(P, N, B)
Beam $:= \{$*false* $\leftarrow$ *true*$\}$, *BestClause* $:=$ *null*
while *Beam* is not empty do
    NewBeam $:= \emptyset$
    for each clause C in *Beam* do
        for each refinement *Ref* of C do
            if *Ref* is better than *BestClause* and *Ref* is
                statistically significant then
                BestClause $:=$ *Ref*
            if *Ref* is not to be pruned then
                add *Ref* to *NewBeam*
                if size of *NewBeam* $>$ *MaxBeamSize* then
                    remove worst clause from *NewBeam*
    Beam $:=$ *NewBeam*
return *BestClause*

ICL Heuristics

- $n(\overline{C})$= number of interpretations (positive and negative) where C is false
- $n^{-}(\overline{C})$= number of negative interpretation where C is false
- $H(C) = p(-|\overline{C}) = \frac{n^{-}(\overline{C})+1}{n(\overline{C})+2}$ = precision over negative class

Descriptive ILP

- Discovering regularities, patterns
- Example tasks:
  - finding association rules
  - clustering
  - subgroup discovery

Claudien [De Raedt, Dehaspe 97]

- Learning problem: Given
  - a space of possible clausal theories $\mathcal{H}$
  - a set P of interpretations
  - a background theory B
- **Find**: a clausal theory $H \in \mathcal{H}$ such that
  - $\forall p \in P, B \cup p \models H$
  - H is maximally specific

Example

$p_1 = \{female(liz), male(richard),$
$gorilla(liz), gorilla(richard)\}$
$p_2 = \{female(ginger), male(fred),$
$gorilla(ginger), gorilla(fred)\}$
If $\mathcal{H}$ contains only range-restricted, constant-free clauses a solution is:
$gorilla(X) \leftarrow female(X)$
$gorilla(X) \leftarrow male(X)$
$male(X) \vee female(X)$
$\leftarrow male(X), female(X)$

Claudien Algorithm

ClausalDiscovery(E, B)
$H := \emptyset$
$Beam := \{false \leftarrow true\}$
while *Beam* is not empty do
    delete from *Beam* the first clause C
    if C is true on E then
        $H := H \cup \{C\}$
    else
        for all $C' \in \rho(C)$ for which not prune(C') do
            $Beam := Beam \cup \{C'\}$
return H

Pointers

- ILPnet2
  - `http://www.cs.bris.ac.uk/~ILPnet2/`
  - `http://www-ai.ijs.si/~ilpnet2/`
- KDnet `http://www.kdnet.org/`
- Books:
  - [Lavrac, Dzeroski 94]: freely available in pdf from `http://www-ai.ijs.si/SasoDzeroski/ILPBook/`
  - [Bergadano et al. 96]
  - [Dzeroski, Lavrac 01]

Bibliography

- [Bergadano et al. 96] F. Bergadano and D. Gunetti, Inductive Logic Programming - From Machine Learning to Software Engineering, MIT Press, 1996
- [Blockeel, De Raedt 98] H. Blockeel and L. De Raedt, Top-down Induction of First-order Logical Decision Trees, Artificial Intelligence, 101, 1998
- [Bratko, Muggleton 95] I. Bratko and S.H. Muggleton, Applications of Inductive Logic Programming, Communications of the ACM, 38(11):65-70, 1995
- [Cameron-Jones et al. 94] R. M. Cameron-Jones and J. Ross Quinlan, Efficient Top-down Induction of Logic Programs, SIGART, 5, 1994
- [De Raedt, Bruynooghe 93] L. De Raedt and M. Bruynooghe, A Theory of Clausal Discovery, Proceedings of the 13th International Joint Conference on Artificial Intelligence, 1993
- [De Raedt, Dehaspe 97] L. De Raedt and L. Dehaspe Clausal Discovery, Machine Learning, 26, 1997.
- [De Raedt, Van Laer 95] L. De Raedt and W. Van Laer, Inductive Constraint Logic, Proceedings of the 6th Conference on Algorithmic Learning Theory, 1995

Bibliography

- [Dolsak et al. 94] B. Dolsak, I. Bratko and A. Jezernik Finite Element Mesh Design: An Engineering Domain for ILP Application, Proceedings of the 4th International Workshop on Inductive Logic Programming, 1994
- [Dzeroski et al. 94] S. Dzeroski, L. Dehaspe, B. Ruck and W. Walley, Classification of river water quality data using machine learning, Proceedings of the 5th International Conference on the Development and Application of Computer Techniques to Environmental Studies, 1994
- [Dzeroski et al. 96] S. Dzeroski, S. Schulze-Kremer, K. Heidtke, K. Siems and D. Wettschereck, Applying ILP to diterpene structure elucidation from C NMR spectra, Proc. 6th International Workshop on Inductive Logic Programming, 1996
- [Dzeroski, Lavrac 01] S. Dzeroski and N. Lavrac, editors, Relational Data Mining Springer, Berlin, 2001
- [Finn et al. 98] P. Finn, S. Muggleton, D. Page and A. Srinivasan. Pharmacophore discovery using the inductive logic programming system Progol. Machine Learning, 30:241-271, 1998
- [King et al. 95] R. D. King, A. Srinivasan and M. J. E. Sternberg, Relating chemical activity to structure: an examination of ILP successes. New Gen. Comput., 1995

Bibliography

- [King et al. 96] R. D. King, S. H. Muggleton, A. Srinivasan and M. Sternberg, Structure-activity relationships derived by machine learning: the use of atoms and their bond connectives to predict mutagenicity by inductive logic programming, Proceedings of the National Academy of Sciences, 93:438-442, 1996
- [Lavrac, Dzeroski 94] N. Lavrac and S. Dzeroski, Inductive Logic Programming Techniques and Applications, Ellis Horwood, 1994
- [Muggleton 95] S. H. Muggleton, Inverse Entailment and Progol, New Gen. Comput., 13:245-286, 1995
- [Muggleton 99] S.H. Muggleton, Scientific knowledge discovery using Inductive Logic Programming. Communications of the ACM, 42(11):42-46, 1999
- [Muggleton, De Raedt 94] S.H. Muggleton and L. De Raedt, Inductive logic programming: Theory and methods, Journal of Logic Programming, 19,20:629-679, 1994
- [Muggleton, Feng 90] S. H. Muggleton and C. Feng, Efficient induction of logic programs, Proceedings of the 1st Conference on Algorithmic Learning Theory, 1990

Bibliography

- [Muggleton et al. 92] S. Muggleton, R. D. King, and M. J. E. Sternberg Predicting protein secondary structure using inductive logic programming, Protein Engineering, 5:647–657, 1992
- [Plotkin 70] G.D. Plotkin, A note on inductive generalisation, Machine Intelligence 5, Edinburgh University Press, 1970
- [Plotkin 71] G.D. Plotkin, Automatic Methods of Inductive Inference, PhD thesis, Edinburgh University, 1971
- [Quinlan 90] J. R. Quinlan, Learning logical definitions from relations, Machine Learning, 5:239– 266, 1990
- [Quinlan 91] J. R. Quinlan, Determinate literals in inductive logic programming, Proceedings of Twelfth International Joint Conference on Artificial Intelligence, Morgan Kaufmann, 1991
- [Quinlan, Cameron-Jones 93] J. R. Quinlan and R. M. Cameron-Jones, FOIL: A Midterm Report, Proceedings of the 6th European Conference on Machine Learning, Springer-Verlag, 1993

Bibliography

- [Quinlan, Cameron-Jones 95] J. R. Quinlan, and R. M. Cameron-Jones, Induction of Logic Programs: FOIL and Related Systems, New Generation Comput. 13(3&4): 287-312, 1995
- [Riguzzi 06] F. Riguzzi, ALLPAD: Approximate Learning Logic Programs with Annotated Disjunctions, Inductive Logic Programming, 2006
- [Srinivasan et al. 97] A. Srinivasan, R.D. King, S.H. Muggleton and M. Sternberg. Carcinogenesis predictions using ILP, Proceedings of the Seventh International Workshop on Inductive Logic Programming, pages 273-287, 1997
- [Srinivasan et al. 95] A. Srinivasan, S.H. Muggleton and R.D. King, Comparing the use of background knowledge by inductive logic programming systems, Proceedings of the Fifth International Inductive Logic Programming Workshop, 1995
- [Turcotte et al. 01] M. Turcotte, S. Muggleton and M. J. E. Sternberg, The effect of relational background knowledge on learning of protein three-dimensional fold signatures, Machine Learning, 43(1/2):81–95, 2001
- [Van Laer et al. 97] W. Van Laer, L. De Raedt and S. Dzeroski, On Multi-class Problems and Discretization in Inductive Logic Programming, 10th International Symposium on Foundations of Intelligent Systems, ISMIS, 1997