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
john	35	m	ca
mary	25	f	ca
ann	29	f	wa
steve	31	m	va

respond

Name
ann

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 with respect to generalization)
- 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 $\{h, \mathit{not}\ b_1, \dots, \mathit{not}\ b_n\}$
- 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

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

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 $C\theta \subseteq D$

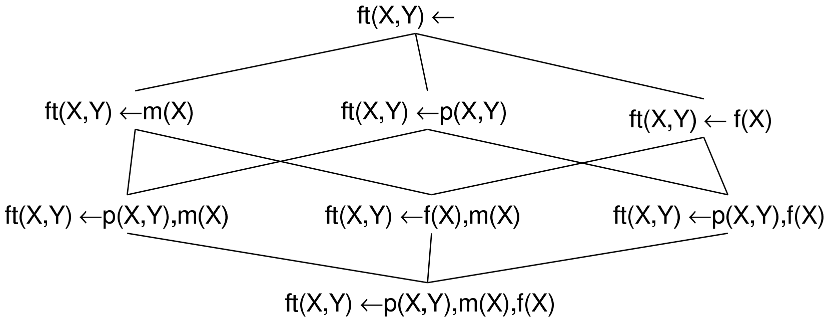
In Practice

- 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

- $lgg(C, D) = \{lgg(L, K) | L \in C, K \in D \text{ and } lgg(L, K) \text{ is defined}\}$
- 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: $WRAcc = P(C)(P(+|C) - P(+))$, where $P(C) = n(C)/n$

FOIL [Quinlan 90]

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

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 (*bottom clause*) $\perp$ 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

Bottom Clause $\bot$ [Muggleton 95]

- Most specific clause covering an example e
- Form: $e \leftarrow B$
- B: set of ground literals that are true regarding the example e
- B obtained by considering the constants in e and querying the predicates of the background for true atoms regarding these constants
- A list of constants is kept, it is enlarged with those in the answers to the queries and the procedure is iterated a user-defined number of times
- Example:

$e = father(john, mary)$
$B = \{parent(john, mary), parent(david, steve),$
$parent(kathy, mary), female(kathy), male(john), male(david)\}$
$\bot = father(john, mary) \leftarrow$
$parent(john, mary), male(john), parent(kathy, mary), female(kathy).$

Learning from Interpretations

- Interpretation = set of ground atoms.
- Aim: learning a classifier for logical interpretations
- Classifier: a set of disjunctive clauses T
- 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 I is positive if all the clauses of T are true in the interpretation ($I \models T$)
  - an interpretation I is negative if there exists at least one clause of T that is false in it ($I \not\models T$)
- A clause C is true in an interpretation I ($I \models C$) 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

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

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

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-ai.ijs.si/~ilpnet2/`
- Books:
  - N. Lavrac and S. Dzeroski, Inductive Logic Programming Techniques and Applications, Ellis Horwood, 1994, freely available in pdf from `http://www-ai.ijs.si/SasoDzeroski/ILPBook/`
  - L. De Raedt, Logical and relational learning, Springer, 2008
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