Logical & Relational Learning (1):
Introduction to Inductive Logic Programming (ILP)

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• Introduction to Machine Learning
• Logical & Relational Learning
• Inductive Logic Programming (ILP)

Outline

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   • ILP Applications

References

Books, articles and reports :

• Saso Dzeroski, James Cussens, Suresh Manandhar, « An Introduction to Inductive Logic Programming and Learning Language in Logic ».

Courses/tutorials :

• Course of Krishnaprasad Thirunarayan (T.K.Prasad), Wright University, Dayton, Ohio (USA).
• Cours de N. Lavrac, J. Stefan Institute, Ljbljan (Slovenia).

1. Introduction to Machine Learning
   • Machine Learning Problem
   • Supervised & Unsupervised ML
   • Structure Learning Vs Parameters Learning
   • Input and output representations in ML
Machine Learning: Definitions

- **Machine Learning (ML) is:**
  - The process by which relatively permanent changes occur in behavioural potential as a result of experience. (Anderson)
  - Learning is constructing or modifying representations of what is being experienced. (Michalski)
  - A computer program is said to learn from experience $E$ with respect to some class of tasks $T$ and performance measure $P$, if its performance at tasks in $T$, as measured by $P$, improves with experience $E$. (Mitchell)
  - ...

Supervised Machine Learning Problem

- Suppose we want that a machine learns from a set of examples from a certain domain, concerning specific features of this domain and output related,
- The task this machine have to do is to devise a mapping from these features to the output (label of class) this mapping is also called model,
- A machine learning system can learn a model using a learning algorithm considering a training dataset, which consists of examples for which the output is already known:

```
<table>
<thead>
<tr>
<th>Domain</th>
<th>Features</th>
<th>Data</th>
<th>Model</th>
<th>Output</th>
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</table>
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“Machine learning is concerned with using the right features to build the right models that achieve the right tasks” [Flach, 2012]

Supervised & Unsupervised ML

- **Supervised ML** (naive Bayes classifiers, SVM, Kernels, ILP, …):
  - task of inferring a function from a set of labeled training examples $(x_i, Y_i)$
  - each example is a pair of an input (a vector) and a desired output
  - an supervised learning algorithm:
    - analyzes the training data and produces an inferred function which try to determine the class labels for training examples
    - generalize from the training data to unseen examples
    - according to a set of assumptions (inductive bias) to predict outputs given inputs that it has not encountered.
  - **Unsupervised ML** (clustering, neural networks, …)
    - task of inferring a function to describe hidden structure from a set of unlabeled training examples (without desired output)
    - there is no objective evaluation of the accuracy of the structure that is output by the relevant algorithm

Structure & Parameters Learning in ML

We distinguish 2 types of learning:

- **Parameters Learning:**
  - Given the structure (the rules) of this learning model $M$ and we just want to infer the relevant parameters of $M$ from a training set of examples (Ex: parameters of a classifier or variables of a rule or a set of rules, …)

- **Structure Learning:**
  - This learning consists to learn:
    - The structure of the learning model $M$ from a training set of examples (Ex: a classifier, a rule or a set of rules, …)
    - The relevant parameters of $M$ (Ex: parameters of a classifier, variables of rule or a set of rules, …)

  Complexity of Structure learning > Complexity of Parameter learning
Input and Output Representations in ML

Input representation:
- The inputs in the learning process, training set examples, can be represented as:
  - A propositional representation (Ex: a vector, …)
  - A symbolic representation: (Ex: in First Order Logic, in Prolog, …)

Output representation:
- The outputs of the learning process, a model (structure + parameters) can be expressed in:
  - A numerical value: probabilities: Ex: \(P(X_i /\text{Class}_i)\), regressions, …
  - A symbolic representation:
    - a propositional rule (without variable), decision tree, …
    - a first order rule with variables (Prolog rules)

Forms of Reasoning

- Deduction: From causes to effect (logic inference)
  - fact a, rule a => b
  - INFER b ("First-order logic")

- Induction: From correlated observations to rules (Learning)
  - observe correlation between a1, b1, ... an, bn
  - LEARN a -> b

- Abduction: From effects to possible causes (Explanation)
  - rule a => b, observe b
  - AN EXPLANATION a

We will now consider only Deduction and Induction.
### Inductive Reasoning

**Induction illustration in “Rock-paper-scissors” game**

- **Inductive Reasoning**: can learn a rule from examples and a set of facts which describe the example (or Background Knowledge - BK)

| Facts (BK) | plays(1, ines, rock)  
|           | plays(1, joana, scissors) |
| +          |                             |
| Examples   | beats(1, ines, joana)       |
| Rules      | beats(Round, PlayerA, PlayerB) :  
|           | - plays(Round, PlayerA, rock),  
|           | plays(Round, PlayerB, scissors) |

### Predictive versus Descriptive Induction

**Predictive induction**: Inducing classifiers, aimed at solving classification/prediction tasks
- **Classification rule learning, Decision tree learning, ...**
- **Bayesian classifier, ANN, SVM, ...**

> Data analysis through hypothesis generation and testing

**Descriptive induction**: Discovering regularities, uncovering patterns, aimed at solving KDD tasks
- **Symbolic clustering, Association rule learning, Subgroup discovery, ...**

> Exploratory data analysis
Logical and Relational Learning

Goal: to find a hypothesis h, i.e., a logic program, from a set of positive & negative examples:

- Given:
  - a set of training examples $T$ expressed in a language chosen for representing the examples $L_E$,
  - a background knowledge $B$,
  - a hypothesis language $L_h$ that specifies the clauses that are allowed in the hypotheses set $H$,
  - a relation covers($e$, $H$, $B$) which determines the classification of an example $e$ with respect to $H$ and $B$,

- Find a hypothesis $h \in H$ that:
  - covers all positive training examples and
  - none of the negative ones
  with respect to background theory $B$.

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3. Inductive Logic Programming (ILP)

- Definition of Inductive Logic programming
- Predictive ILP and Descriptive ILP
- ILP interests: multiples relations and structured data
- Rule learning in ILP: global process
- ILP Systems Strategies for Hypothesis Search
- ILP Applications

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Logical and Relational Learning: learning settings

- Specific learning setting is determined by $L_E$ language together with the covers relation [De Raedt, 1997]
- Most popular learning settings are:
  - Learning from entailment [Plotkin 1970]: the examples are definite clauses:
    - an hypothesis $h$ covers an example $e$ with respect to the background knowledge $B$ if and only if $B \cup H \models e$
    - an example can consist of just a single fact.
  - Learning from interpretations [De Raedt and Dzeroski, 1994]: the examples are Herbrand interpretations:
    - an hypothesis $h$ covers an example $e$ with respect to the background knowledge $B$ if and only if $e$ is a model of $B \cup H$
    - all facts that hold in the example are known, more information is available to the learner.

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Inductive Logic Programming – ILP

- ILP is a technique related to Logical and Relational Learning:
  - At the intersect of Machine Learning & Logic Programming domains

- Which learns logic rules from examples and background knowledge (BK)
  - $Ex$ : learn the rule for grand parents, given background knowledge of parents and examples of grandparents
- Induces rules which explain examples and BK
- based on Logic Programming (Prolog)
- ILP can be used for:
  - Classification and Prediction
  - to interface with experts of other areas of knowledge
Predictive ILP: Classification (1)
(Source N. Lavrac)

- **Given:**
  - A set of observations:
    - a set of *positive examples* \( E^+ \)
    - a set of *negative examples* \( E^- \)
  - A *Background Knowledge* \( B \)
  - An hypothesis language \( L_H \)

- **Find an hypothesis** \( H \in L_H \) such that (given \( B \)) \( H \) covers ALL positive and NO negative examples

- **In logic,** find \( H \) such that:
  - \( \forall e \in E^+: B \cup H \models e \) (\( H \) is complete)
  - \( \forall e \in E^-: B \cup H \not\models e \) (\( H \) is consistent)

- **In ILP,** \( E \) are ground fact, \( B \) and \( H \) are (set of) *definite clauses.*

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Predictive ILP: Classification (2)
(Source N. Lavrac)

- **Given:**
  - A set of observations:
    - a set of *positive examples* \( E^+ \)
    - a set of *negative examples* \( E^- \)
  - A *Background Knowledge* \( B \)
  - An hypothesis language \( L_H \)

- **Find an hypothesis** \( H \in L_H \) such that (given \( B \)) \( H \) is optimal w.r.t. some quality criterion: max. predictive accuracy \( A(H) \)

- (instead find a hypothesis \( H \in L_H \) such that (given \( B \)) \( H \) covers ALL positive and NO negative examples)

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Descriptive ILP: Discovery
(Source Lavrac)

- **Given:**
  - A set of observations:
    - a set of *positive examples* \( E^+ \)
  - A *Background Knowledge* \( B \)
  - An hypothesis language \( L_H \)

- **Find:** Maximally specific hypothesis \( H \in L_H \) such that (given \( B \)) \( H \) covers ALL positive examples

- **In logic,** find \( H \) such that \( \forall c \in H, c \text{ is true in some preferred model of } B \cup E \) (e.g. least Herbrand model \( M(B \cup E) \))

- **In ILP,** \( E \) are ground fact, \( B \) and \( H \) are (set of) *general clauses.*

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A Sample Problem: Learning of Family Relations (1)
(Source Lavrac)

**Observations:**

\[
E^+ = \{ \text{daughter(mary,ann), daughter(eve,tom)} \}
\]
\[
E^- = \{ \text{daughter(tom,ann), daughter(eve,ann)} \}
\]

**Background Knowledge:**

\[
B = \{ \text{mother(ann,mary), mother(ann,tom), father(tom,eve), father(tom,ian), female(ann), female(mary), female(eve), male(pat), male(tom), parent(X,Y) ← mother(X,Y), parent(X,Y) ← father(X,Y)} \}
\]
A Sample Problem: Learning of Family Relations (2)
(Source Lavrac)
\[ E^+ = \{ \text{daughter(mary, ann)}, \text{daughter(eve, tom)} \} \]
\[ E^- = \{ \text{daughter(tom, ann)}, \text{daughter(eve, ann)} \} \]
\[ B = \{ \text{mother(ann, mary), mother(ann, tom), father(tom, eve), father(tom, ian), female(ann), female(mary), female(eve), male(pat), male(tom), parent(X, Y) \leftarrow \text{mother(X, Y)}, \text{parent}(X, Y) \leftarrow \text{father}(X, Y) \} \]

Predictive ILP: induce a definite clause:
\[ \text{daughter}(X, Y) \leftarrow \text{female}(X), \text{parent}(Y, X) \]

Descriptive ILP: induce a set of (general) clauses:
\[ \text{daughter}(X, Y) \leftarrow \text{female}(X), \text{mother}(Y, X) \]
\[ \text{daughter}(X, Y) \leftarrow \text{female}(X), \text{father}(Y, X) \]

ILP interest: Multiples relations
- Most ML techniques cannot use more than one relation:
  - e.g., decision trees, neural networks, ...
- ILP technique permit to use multiple relations:
  - Ex:
    - Given known relations:
      \[ \text{father}(\text{Old}, \text{Young}) \text{ and } \text{mother}(\text{Old}, \text{Young}) \]
    \[ \text{male}(	ext{Somebody}) \text{ and } \text{female}(	ext{Somebody}) \]
  - ILP can learn new relations:
    \[ \text{parent}(X, Y) \leftarrow \text{father}(X, Y) \]
    \[ \text{parent}(X, Y) \leftarrow \text{mother}(X, Y) \]
    \[ \text{brother}(X, Y) \leftarrow \text{male}(X), \text{father}(Z, X), \text{father}(Z, Y). \]

ILP interest: Structured Data (1)
- Example of East-West trains (Michalski):

Question: What makes a train to go eastward?
ILP interest: Structured Data (3)

Induction of a classifier for the East-West trains example:

- **BK:***
  - relation *has_car*
    
    Ex : has_car(t1, c11), ...
  - relation *car_properties* (length, roof, shape, axle, roof, ...)
    
    Ex : length(c11, short), ...

- **Examples:**
  
  the trains t1 to t10

- **Classes:**
  
  east, west

- **Possible Hypothesis (Theory):***
  
  east(T) :- has_car(T, C), length(C, short), roof(C, _)

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Rule learning in ILP: global process (1)

**Problem: learn *grandparent* rule:**

- **Background knowledge *BK*:***
  
  parent_of(charles, george)  
  parent_of(george, diana)  
  parent_of(bob, harry)  
  parent_of(harry, elizabeth).

- **Positive examples *E+:***
  
  grandparent_of(charles, diana)  
  grandparent_of(bob, elizabeth).

- **Generate hypothesis *H*:***
  
  grandparent_of(X,Y) :- parent_of(X,Z), parent_of(Z,Y).

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Rule Learning in ILP: global process (2)

**How to come up with a rule for *grandparent_of(X,Y)*?**

1. Take the example *grandparent_of(bob,elizabeth).*
2. Find the subset of Background Knowledge (BK) relevant to this example:
   
   parent_of(bob, harry)  
   parent_of(harry, elizabeth) .
3. **Form a rule** from these facts:
   
   grandparent_of(bob,elizabeth) :- parent_of(bob, harry), parent_of(harry, elizabeth).
4. **Generalize the rule:**
   
   grandparent_of(X,Y) :- parent_of(X,Z), parent_of(Z,Y).
5. **Check if this rule is valid** for the positive and not valid for the negative examples

  => Elaboration and Exploitation of the Hypothesis Space

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Rule Learning in ILP: global process (3)

**Subtasks performed by an ILP implementation regarding ILP as a search problem in the Hypothesis Space:**

1. Structuring the Hypothesis Space,
2. Searching the Hypothesis Space,
3. Bounding the Search,
4. Evaluating the Hypotheses.
Rule Learning in ILP: global process (4)

Procedure: traverses the hypothesis space, generating and testing the candidate hypothesis implemented by a covering algorithm which construct iteratively a set of clauses:

Covering (E)

Input: set of examples E
Output: a set of consistent rules

1. Learn_Rules = Ø
2. E' = Positive(E)
3. while E' ≠ Ø
4. R = learn_rule(E')
5. Learn_Rules = Learn_Rules ∪ R
6. E' = E' - {examples covered by R}
7. end while
8. return Learn_Rules

1. Search starts with a very general rule (clause with no conditions in the body), 2. Proceeds to add literals (conditions) to this clause until it only covers positive examples, i.e., the clause is consistent.

Starting with an empty set of rules (Line 1), the algorithm then generates and evaluates a clause on the positive examples (Line 4), if this clause satisfies some criteria, it adds the clause to the hypothesis (Line 5) and removes the positive examples covered by the clause (Line 6).

These steps are repeated until all positive examples have been covered (loop while Line 3).

The learn_rule(e) procedure in Line 4 constructs individual clauses by (heuristically) searching the space of possible clauses, structured by a specialization or generalization operator.

ILP Systems Strategies for Hypothesis Search (1)

- **Prolog** [Muggleton, 1995]: an iterative top-down ILP system that performs batch learning: all of the examples and the BK must be defined before starting the algorithm.
- **ALEPH** [Srinivasan] uses functionalities from various ILP systems like: Prolog, FOIL, FORS, Indlog, MIDOS, SRT, Tilde and WARM ...
- **GILPS** [Santos 2010]: implements TopLog, ProGolem, The BK and mode declarations definitions of GILPS are identical to Aleph and Prolog.
- **Golem** [Muggleton & Feng, 1990]: a bottom-up ILP system, which constrains the search space with the relative least general generalization (rlgg) [Plotkin, 1971].
- **Progolem** (Muggleton et al., 2010): Combine Golem and Prolog strategies.
- **Toplog** (Muggleton et al., 2008): uses a declarative bias called Top-Directed Hypothesis Derivation (TDHD), where each clause issued as a candidate hypothesis must be derived from a precise logical program called top theory T.

Some ILP systems (2)

- **FOIL** [Quinlan93] learns multiple predicates from a non-interactive and non-incremental mode, realizing a top-down search in the hypothesis space
- **MIS** [xxx]: an interactive system and theory reviewer. It learns a definition of multiple predicates in a incremental way. Realize top-down search and it was the first ILP system that accept background knowledge from an intentional and extensional way.
- **Tilde** [xxx]: it’s a learning system based on decision trees. These trees can be used to classify new examples or transformed in a logical program.
- **LINUS** [xxx]: an empirical ILP system, non-interactive and non-incremental. It transforms ILP systems to a attribute-value representation.
- ...

Characteristics of various ILP systems

(Source: [Conceição 2008])

<table>
<thead>
<tr>
<th>System</th>
<th>TD</th>
<th>BU</th>
<th>Predictive</th>
<th>Descriptive</th>
<th>Inc</th>
<th>N-Inc</th>
<th>Int</th>
<th>N-Int</th>
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- **TD**: if the system uses a top-down search
- **BU**: if the system uses a bottom-up search
- **Predictive**: if the finding task of knowledge is predictive : then classification rules can be generated
- **Descriptive**: if the finding task of knowledge is descriptive : then only true properties from the examples are observed
- **Inc and N-Inc**: if the system uses incremental or non-incremental learning, respectively
- **Int and N-Int**: if the system is the type interactive or non-interactive, respectively
- **Multi-Pred**: if the system can learn multiple predicates.
Applications of ILP (1)

- Application in NLP (Natural Language Processing)
  - Information extraction from text (Named Entity Recognition, Relation Extraction, ...)
  - Constructing Biological Knowledge Bases by Extracting Information from Text Sources
- ... 

- Applications to Chemoinformatics and Bioinformatics
  - Learning drug structure-activity rules:
  - Learning rules for predicting mutagenesis, carcinogenesis
  - Learning to identify pharmacophores on small molecules (with Pfizer UK and Prolifix Ltd. Made available soon)
  - Learning rules for predicting protein secondary structure
  - Learning qualitative models for functional genomics (with the Computational Biology Group, Aberystwyth)
  - Learning to identify neuropeptide precursors (with the Machine Learning Group, University of York and the Bioinformatics Group, SmithKline-Beecham. Made available soon)
- ...

Applications of ILP (2)

- Applications to Medicine
  - Learning rules for selecting the best embryos for transfer in In Vitro fertilisation
  - Learning to identify diabetics susceptible to renal disease
  - Learning qualitative models of the human lung
  - ...

- Applications to other areas
  - Learning rules from chess databases
  - Inductive Learning of Chess Rules Using Progol
  - Learning rules for finite element mesh design
  - Learning diagnostic rules for qualitative models of satellite power supplies
  - Learning qualitative models of the U-tube system
  - Learning to identify over-performing stocks
  - Learning simplified civil-service procedures
  - ...

- More from UT-ML group (Ray Mooney)

ILP and Natural Language Processing (NLP)

Application of ILP to NLP led to the research domain of Learning Language in Logic (LLL), intersection of Machine Learning (ML), NLP and Computational Logic (CLo):

- ML
- ILP
- CLo
- LLL
- DDNL
- LG
- NLP

Source [Dzeroski et al., 1999]
(with CLo = computational logic, ML = machine learning, DDNL = data-driven NLP, LG = logic grammars, NLP = natural language processing, ILP = inductive logic programming.)

A contribution : OntoILPER [Lima el al., 2013] using GIPS ILP system [Santos 2010]

ILP: Some Limitations ...

- Limitation related to Prolog language:
  - Specification of a finite set ensemble of constants,
    - Numerical domains have to be borned.
    - If $D = \{0, 1, 2, 3\}$, what is value of succ(3, ?)
  - Inadequate representation of numerical data.

- Time processing:
  - Parallel Prolog, Map Reduce, ...

- Unable to treat uncertainty:
  - PILP (Probabilistic ILP)