Introduction to Inductive Logic Programming

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Outline

1 Introduction
   • Motivation
   • Objectives
   • Overview
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1. Introduction
   - Motivation
   - Objectives
   - Overview

2. Background Knowledge
   - Propositional (Classical) Logic
   - First–Order Logic
   - Logic Programming
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3. Inductive Logic Programming
   - Definitions
   - Progol
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4. Neural–Symbolic Systems
   - Introduction
   - C–IL2P
   - CILP++
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5 Conclusion
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5. Conclusion
Thinking and Explaining

- Imagine a father teaching his little daughter how to drink a glass of water
Thinking and Explaining

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  - He needs to use a proper language to teach her each step involved
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  - It should be as clear as possible
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- The representation of each object should be good enough for that
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- Which would fit best?
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- Which would fit best?
  - “To drink water, you need to grab a glass and use a sink”
Thinking and Explaining

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  - He needs to use a proper language to teach her each step involved
  - It should be as clear as possible
  - The representation of each object should be good enough for that

- Which would fit best?
  - “To drink water, you need to grab a glass and use a sink”
  - water, glass $\in [0, 1]$, threshold $= 2$, drinking $= (\text{water} + \text{glass}) \geq \text{threshold}$
Symbolic Arguments

“The Neural Networks did perform well (...). However, (...) they consumed enormous amounts of CPU time and they are sometimes equaled by simple symbolic classifiers” (Weiss and Kapouleas, 1989)
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- “Structured knowledge, is difficult to represent in Neural Networks, contrary to traditional logical models” (Toiviainen, 2000)
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- “Structured knowledge, is difficult to represent in Neural Networks, contrary to traditional logical models” (Toiviainen, 2000)

- “Attempts have been made to explain the behavior of connectionist networks (...). These explanations are, however, at the level of primitive features of the network (...). Explanations on a higher level of knowledge are difficult to achieve” (Toiviainen, 2000)
Connectionistic Arguments

“Connectionist networks are robust. (...) They are resistant to noise and gracefully degrade when they are damaged or overloaded with information” (Smolensky et al., 1992)
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- “Neural Networks are capable of extracting significant features from the training set and using them to process a novel input pattern, thus generalizing better” (Toiviainen, 2000)
Connectionistic Arguments

- “Connectionist networks are robust. (...) They are resistant to noise and gracefully degrade when they are damaged or overloaded with information” (Smolensky et al., 1992)
- “Neural Networks are capable of extracting significant features from the training set and using them to process a novel input pattern, thus generalizing better” (Toiviainen, 2000)
- “Differently from (symbolic) machine learning, (numeric) neural networks perform inductive learning in such a way that the statistical characteristics of the data are encoded in their sets of weights” (Garcez et al., 2009)
Which Means...

- Both paradigms has its own strengths and weaknesses
Which Means...

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• Both are usually better suited on different kinds of applications
Which Means...

- Both paradigms have its own strengths and weaknesses.
- Both are usually better suited on different kinds of applications.
- **Both are important and relevant to a complete reasoning model.**
The World Without Logic (1)

Knowledge Representation:

With Logic:
IF (I Study) AND NOT (Evil Teacher) → (I Will Pass)

Without Logic (eg. one-layer NN):
\[ W_{\text{study, pass}} = 0.989; \]
\[ W_{\text{evilTeacher, pass}} = -0.966 \]
The World Without Logic (2)

- I am sleepy,
- I am a little tired,
- I am not ok....

- 5.5345,
- 0.5643e^{123},
- -9.7424...

With Logic

Without Logic
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This Talk’s Goals

- Formally introduce Inductive Logic Programming (ILP) and its theoretical foundations
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- Give an overall “feeling” of how it works
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- Formally introduce Inductive Logic Programming (ILP) and its theoretical foundations
- Give an overall “feeling” of how it works
- Briefly point out some alternative applications of ILP
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5. Conclusion
Background Knowledge, briefly explaining Propositional and First–Order Logics
Remainder Of The Talk

- **Background Knowledge**, briefly explaining Propositional and First–Order Logics
- **Inductive Logic Programming**, which will show the basic ILP concept
Background Knowledge, briefly explaining Propositional and First–Order Logics

Inductive Logic Programming, which will show the basic ILP concept

Some Relevant Systems that uses ILP, introducing the Connectionist and Inductive Learning and Logic Programming, C–IL2P
Background Knowledge, briefly explaining Propositional and First–Order Logics

Inductive Logic Programming, which will show the basic ILP concept

Some Relevant Systems that uses ILP, introducing the Connectionist and Inductive Learning and Logic Programming, C–IL2P

Conclusion, to enclose everything that has been presented and add some final remarks
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Types of Reasoning

- **Deductive Reasoning:** given a background theory, *what is possible to be inferred from it?*
Types of Reasoning

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- **Inductive Reasoning**: given a background theory and a set of examples, what kinds of new theories can be inferred?
Types of Reasoning

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- **Inductive Reasoning**: given a background theory and a set of examples, **what kinds of new theories can be inferred?**
- **Abductive Reasoning**: given a background theory and a set of examples, **what kinds of facts can explain them?**
Types of Reasoning

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- **Abductive Reasoning**: given a background theory and a set of examples, what kinds of facts can explain them?
- Deductive systems are clearly different from the other two, but inductive and abductive ones are somewhat similar
Types of Reasoning

- **Deductive Reasoning**: given a background theory, what is possible to be inferred from it?
- **Inductive Reasoning**: given a background theory and a set of examples, what kinds of new theories can be inferred?
- **Abductive Reasoning**: given a background theory and a set of examples, what kinds of facts can explain them?
- Deductive systems are clearly different from the other two, but inductive and abductive ones are somewhat similar.
- In fact, under certain circumstances, an inductive task can be transformed into an abductive one and vice-versa.
Syntax

- **Atom**: upper-case letter (P, Q, R, ...), \( \bot \) or \( T \)
Syntax

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Syntax

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- **Logical Negation**: $\neg$
- **Literal**: atom, preceded (**negative literal**) or not (**positive literal**) by $\neg$
- **Connectives**: 
Syntax

- **Atom**: upper–case letter (P, Q, R, ...), ⊥ or T
- **Logical Negation**: ¬
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- **Connectives**:
  - ∧ (and): \( P \land Q \)
Syntax

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- **Logical Negation:** \( \neg \)
- **Literal:** atom, preceded **(negative literal)** or not **(positive literal)** by \( \neg \)
- **Connectives:**
  - \( \land \) (and): \( P \land Q \)
  - \( () \) (parenthesis): \( (P \land Q) \)
Syntax

- **Atom**: upper-case letter ($P, Q, R, ...$), $\bot$ or $T$
- **Logical Negation**: $\neg$
- **Literal**: atom, preceded (negative literal) or not (positive literal) by $\neg$
- **Connectives**:
  - $\land$ (and): $P \land Q$
  - () (parenthesis): $(P \land Q)$
  - $\lor$ (or): $R \lor (P \land Q)$
Syntax

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- **Connectives**:
  - ∧ (and): P ∧ Q
  - () (parenthesis): (P ∧ Q)
  - ∨ (or): R ∨ (P ∧ Q)
  - → (implication): (R ∨ (P ∧ Q)) → S
Syntax

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  - ↔ (double-implication): (((R ∨ (P ∧ Q)) → S) ↔ T)
Syntax

- **Atom**: upper-case letter (P, Q, R, ...), ⊥ or T
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  - → (implication): (R ∨ (P ∧ Q)) → S
  - ↔ (double-implication): ((R ∨ (P ∧ Q)) → S) ↔ T
- **Clause**: one or more literals connected through zero or more connectives, eg. ((R ∨ (P ∧ Q)) → S) ↔ T
Syntax

- **Atom**: upper-case letter ($P, Q, R, ...$), $\bot$ or $T$
- **Logical Negation**: $\neg$
- **Literal**: atom, preceded (negative literal) or not (positive literal) by $\neg$
- **Connectives**:
  - $\land$ (and): $P \land Q$
  - () (parenthesis): $(P \land Q)$
  - $\lor$ (or): $R \lor (P \land Q)$
  - $\rightarrow$ (implication): $(R \lor (P \land Q)) \rightarrow S$
  - $\leftrightarrow$ (double–implication): $((R \lor (P \land Q)) \rightarrow S) \leftrightarrow T$
- **Clause**: one or more literals connected through zero or more connectives, eg. $((R \lor (P \land Q)) \rightarrow S) \leftrightarrow T$
- **Theory**: set of one or more clauses, representing a knowledge domain
Semantics

- An atom can be assigned true or false
Semantics

- An atom can be assigned *true* or *false*
- Given a clause $C$, a clause interpretation for $C$ consists of truth-value assignments for each of its atoms:
  \[ I_C : P_1^C, \ldots, P_i^C \mapsto \{ \text{true}, \text{false} \} \]
Semantics

- An atom can be assigned **true** or **false**
- Given a clause $C$, a clause interpretation for $C$ consists of truth–value assignments for each of its atoms:
  
  $$I_C: P_{i_1}^C, \ldots, P_{i_l}^C \mapsto \{true, false\}^{l}$$

- Given a theory $B = C_1, \ldots, C_m$, an interpretation for $B$ is an assignment of truth values for each of its atoms:
  
  $$I_B: P_{i_1}^{C_1}, \ldots, P_{i_n}^{C_m} \mapsto \{true, false\}^{n}$$
Semantics

- An atom can be assigned **true** or **false**

- Given a clause $C$, a **clause interpretation** for $C$ consists of truth–value assignments for each of its atoms:
  
  
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- **Models** are interpretations that assigns truth values to a given clause or theory:

  
  $M(C) = I : I(C) \rightarrow true :: M(B) = I : I(B) \rightarrow true$
Semantics

- An atom can be *assigned* true or false
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- **Models** are interpretations that assigns truth values to a given clause or theory:
  \[ M(C) = I : I(C) \mapsto \text{true} :: M(B) = I : I(B) \mapsto \text{true} \]
- Interpretations are often represented in a truth–table format
Connectives Truth Table

<table>
<thead>
<tr>
<th>P</th>
<th>Q</th>
<th>\neg P</th>
<th>P \land Q</th>
<th>P \lor Q</th>
<th>P \rightarrow Q</th>
<th>P \leftrightarrow Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>F</td>
<td>V</td>
<td>F</td>
<td>F</td>
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<td>V</td>
</tr>
</tbody>
</table>

PS: All “v” symbols inside the table are *true* values
A clause $C$ is a **logical consequence** of a theory $B$ if and only if $M(B) \subseteq M(C)$ ($B \models C$)
Logical Consequence

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- Logical consequence is also known as **entailment**: \( B \) *entails* \( C \) if and only if \( M(B) \subseteq M(C) \)
Logical Consequence

- A clause C is a **logical consequence** of a theory B if and only if $M(B) \subseteq M(C)$ ($B \models C$)
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- C is **satisfiable** if $M(C) \neq \emptyset$
Logical Consequence

- A clause $C$ is a **logical consequence** of a theory $B$ if and only if $M(B) \subseteq M(C)$ ($B \vDash C$).
- Logical consequence is also known as **entailment**: $B$ *entails* $C$ if and only if $M(B) \subseteq M(C)$.
- $C$ is **satisfiable** if $M(C) \neq \emptyset$.
- **Refutational consequence**: $B \vDash C$ if and only if $B \cup \{\neg C\}$ is not satisfiable.
A deductive system $DS = (L, AX, R)$ is composed by:

- $L$: used language
- $AX$: logical axioms set
- $R$: a set of inference rules

A proof of a clause $C$ is a set of clauses $DB$, on the system $DS$ ($DB \vdash C$), if and only if, exists a finite sequence of clauses $(D_1, ..., D_n)$ which holds:

1. $D_n = C$
2. For each $i \in \{1, ..., n\}$, one of the following conditions is satisfied:
   - $D_i$ is an instance of $AX$
   - $D_i \in DB$
   - There exists $j, k < i$ in which $D_i$ can be obtained by applying rules of $R$
Deductive Systems

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A **proof** of a clause C is a set of clauses DB, on the system DS (DB ⊢ C), if and only if, exists a finite sequence of clauses (D₁, . . . , Dₙ) which holds:

1. Dₙ = C
2. For each i ∈ [1, n], one of the following conditions is satisfied:
Deductive Systems

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Resolution

- Based on refutational consequence
Resolution

- Based on **refutational consequence**
- Definition:

  \[(R \lor (P \land Q)) \rightarrow S \Rightarrow (\neg R \lor S) \land (\neg P \lor S) \land (\neg Q \lor S)\]
Resolution

- Based on **refutational consequence**
- Definition:
  
  \( L: \text{propositional clauses in conjunctive normal form:} \)
  
  \[ (R \lor (P \land Q)) \rightarrow S \Rightarrow \neg R \lor S \land \neg P \lor S \land \neg Q \lor S \]
Resolution

- Based on **refutational consequence**
- Definition:
  - L: propositional clauses in **conjunctive normal form**:
    \[(R \lor (P \land Q)) \rightarrow S \Rightarrow (\neg R \lor S) \land (\neg P \lor S) \land (\neg Q \lor S)\]
  - AX: \(\emptyset\)
Resolution

- Based on **refutational consequence**
- **Definition:**
  - L: propositional clauses in **conjunctive normal form**:
    \[(R \lor (P \land Q)) \rightarrow S \Rightarrow (\neg R \lor S) \land (\neg P \lor S) \land (\neg Q \lor S)\]
  - AX: ∅
  - R: **propositional resolution** – \{A \lor B; C \lor \neg B\} ⇒ \{A \lor C\}
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5. Conclusion
Description

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Description

- Propositional Logic direct extension, to deal with **predicates** (relations)
- Able to conclude particular features of general characteristics over elements of a given domain
- Able to conclude general features from particularities of single elements of a given domain
- To achieve that, two **quantifiers** were included into propositional logic: \( \forall \) (**universal**) and \( \exists \) (**existential**).
Syntax Modifications

- Terms are consisted of

  - Functional symbols
  - Constants
  - Variables
  - Predicates
  - Quantifiers: ∀ (universal) specifies features that are valid for every individual of the domain, ∃ (existential) specifies features that are valid for at least one individual of the domain
  - Clause: now can have variable quantified by one leftmost quantifier, e.g., ∀x (R(X) ∨ (P(X) ∧ q) → s)
Syntax Modifications

- **Terms** are consisted of
  - **Functional symbols** ⇒ starts with lower-case and can have 0 or more terms \((f(X, a))\)
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  - **Functional symbols** ⇒ starts with lower–case and can have 0 or more terms \((f(X, a))\)
  - **Constants** ⇒ facts, defined by *functions* of arity 0 \((f)\)
Syntax Modifications

- **Terms** are consisted of
  - **Functional symbols** ⇒ starts with lower-case and can have 0 or more terms \((f(X, a))\)
  - **Constants** ⇒ facts, defined by *functions* of arity 0 \((f)\)
  - **Variables** ⇒ represented by upper-case letters \((X)\)
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- **Clause**: now can have variable quantified by one leftmost quantifier, eg. \(∀x((R(X) \lor (P(X) \land q)) \rightarrow s)\)
An atom can be *assigned* one value of a given domain $D$ of instantiations (an *assigned* atom is called *grounded*).
Semantics Modifications

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\textbf{Models} are interpretations that assigns truth values to a given clause or theory
First–Order Resolution

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- Besides the proof, first–order resolution returns all used unifications
First–Order Resolution Step

\[ P(A) \lor Q(A, \text{claire}) \quad \neg P(\text{john}) \lor R(\text{abigail}) \]

\[ \theta = \{ A \mid \text{john} \} \]

\[ Q(\text{john}, \text{claire}) \lor R(\text{abigail}) \]
**First–Order Induction**

- **Inverse Resolution**: “backwards” resolution, from the leaves to the root(s). Notable system: Cigol.
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- New inference rule (given a clause $C_1$ with an literal $A$, we want to find $C_2$ with $\neg A$):
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  (Resolvent - (C_1 - \{A\})\theta_1)\theta_2^{-1} \cup \{\neg A\theta_1\theta_2^{-1}\} \]
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- Immediate problem: whereas you are “going up” on inverse resolution, search space increases drastically
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- The semantical domain used for most logic programs is the _Herbrand Universe_
Prolog

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- SLD–Resolution differs from classical resolution by defining which clauses will be resolved
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Monotonic and Nonmonotonic Logic Programming

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- CWA causes nonmonotonicity
CWA Example

Consider the following theory:

\[ B = \{ \text{Trip(brazil, airplane)}, \text{Trip(cambridge, train)}, \text{Trip(leeds, car)} \} \]
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\[
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If a goal literal \textit{Trip(cambridge, train)} is queried with regard to B, a positive answer will be given.

Otherwise, if it is asked for \textit{Trip(paris, airplane)}, two answers can be obtained, depending if CWA is being used.
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- If it is used, this query would return $\text{false}$.
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Inductive Logic Programming (ILP) is a machine learning technique that conducts supervised inductive concept learning.
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Which means: given a set of labeled examples $E$ and a background knowledge $B$, an ILP system will try to find a hypothesis function $H$ that minimizes a specified loss $\text{loss}(B \cup H, E)$. The obtained $H$ not only classifies new examples but can improve an existing theory.
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In ILP context:

- \( B \): pre-existing definite program
- \( E \): set of grounded atoms of target concept(s), in which labels are truth-values
- \( H \): target definite program that entails most examples of E
- \( \text{loss}(B \cup H, E) \): function of the number of examples entailed by \( B \cup H \), \( E \)
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Task Formalization

- An ILP task can be defined in two ways, depending on the type of learning:
  
  1. **Learning from entailment**: An ILP task is defined as a tuple \(<E, B, L>\), where:
     - \(E\): set of positive and negative literals (examples)
     - \(B\): logic program that defines the background knowledge underlying the task
     - \(L\): set of logic theories that restricts the search space to find a suitable hypothesis (language bias)
  
  2. **Learning from interpretation**: An ILP task is also defined as \(<E, B, L>\), where:
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- ILP systems can build hypothesis following two directions:
  - **Bottom–Up**: starting with the most specific clause (⊥), generalizations can be made to make it cover the positive examples while keeping most negative ones out
  - **Top–Down**: starting with the most general clause (h ←), specializations can be made to eliminate negative examples from the coverage set while maintaining positive ones covered
ILP General Algorithm

- Most ILP systems are based in a **Sequential–Covering** algorithm:

Algorithm 1 Sequential–Covering Algorithm

Require: \( E, B, L \)
Ensure: \( H \)
1: \( E_{\text{cur}} = E \)
2: \( H = \emptyset \)
3: while generalization stopping criterion is satisfied do
4: \( c = h \leftarrow \)
5: while specialization stopping criterion is satisfied do
6: \( c = \text{REFINE}(c, L) \)
7: end while
8: \( H = H \cup c \)
9: \( E_{\text{cov}} = \{ e \in E_{\text{cur}} : B \cup H \models e \} \)
10: \( E_{\text{cur}} = E_{\text{cur}} - E_{\text{cov}} \)
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**REFINE** is a function that varies between ILP systems and chooses or removes bodies from a candidate hypothesis.
Quick Note

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- The way they work and are used depends on the ILP system being used, as well as the language bias L
- For convenience, Progol has been chosen as the system which will illustrate how these dependencies works
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A Brief Summary of Progol

- **Progol** is an ILP system and a Machine Learning algorithm, based on *Inverse Entailment* and *Sequential Covering*, which searches for suited hypothesis in a search space bounded by the most general clause (h ←) and a *Bottom–Clause* (⊥).

Inverse Entailment: \[ B \cup H \models E \Rightarrow B \models H \rightarrow E \Rightarrow B \models \neg E \rightarrow \neg H \]

Sequential Covering: the search for an hypothesis starts from (h ←) and adds iteratively literals that covers the positive examples and do not covers most of the negative ones.

Bottom–Clause: most–specific clause of a restricted space, defined by a single example and L

It uses the following loss function:

\[
\text{loss}_{\text{progol}}(E, B, H) = \sum_{r \in H \models \neg \{e \in E^+ : B \cup H \models e\}} |\{e' \in E^- : B \cup H \models e'\}| + |\{e' \in E^- : B \cup H \models e'\}|
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  - **Sequential Covering**: the search for an hypothesis starts from \((h \leftarrow)\) and adds iteratively literals that covers the positive examples and do not covers most of the negative ones

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**A Brief Summary of Progol**

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  - **Inverse Entailment**: \( B \cup H \models E \Rightarrow B \models H \Rightarrow E \Rightarrow B \models \neg E \Rightarrow \neg H \)
    \( \Rightarrow B \cup \neg E \models \neg H \) (\( H \models \bot \))

  - **Sequential Covering**: the search for an hypothesis starts from \( h \leftarrow \) and adds iteratively literals that covers the positive examples and do not covers most of the negative ones

  - **Bottom–Clause**: most–specific clause of a restricted space, defined by a single example and \( L \)
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  - **Bottom–Clause**: most–specific clause of a restricted space, defined by a single example and L

- It uses the following loss function:

  \[
  \text{loss}^{\text{progol}}(E, B, H) = + \sum_{r \in H} |r| - |\{ e \in E^+ : B \cup H \models e \}| + |\{ e' \in E^- : B \cup H \models e' \}|
  \]
Language Bias Structure

- Progol has two language bias structures:
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  - **Mode Declarations**: can be *head declarations* – modeh(recall, s), or body declarations – modeb(recall, s), where *recall* controls the number of instantiations of a literal and *s* is a ground positive or negative literal, with *placemarkers* which defines if it is an input (+), output (−) or a constant (#), and its type.

Examples:

- `modeh(1, mother_in_law(+woman, −man))`
- `modeb(∗, progenitor_of(+woman, −woman))`
- `modeb(1, wife_of(+woman, −man))`

Determinations:

- `determination(mother_in_law/2, progenitor_of/2)`
- `determination(mother_in_law/2, wife_of/2)`
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    - `determination(mother_in_law/2, wife_of/2)`
Specialization and Generalization Operators

- Uses $\theta - subsumption$: a clause $C$ $\theta - subsumes$ $D$ ($C \prec \theta D$) if exists a substitution $\theta$ in which $C\theta \subseteq D$ holds, eg.:
  
  $C$: $f(A, B) \leftarrow p(B, G), q(G, A)$ $\theta - subsumes$
  
  $D$: $f(a, b) \leftarrow p(b, g), q(g, a), t(a, d)$ through $\theta = \{A/a, B/b, G/g\}$
Specialization and Generalization Operators

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- If $C \prec_\theta D$, then $C \models D$
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- If $C \prec_\theta D$, then $C \models D$

- This means that for a specialization or generalization of a clause $C$, $C \prec_\theta \perp$ ensures that the search space bounds still holds
Variable Chaining

In Progol, every body input variable needs to be an input of a head literal or an output of a previous body literal.
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- An example:

  \[
  \text{modeh}(*, \text{mult}(+\text{real}, +\text{real},-\text{real})) \\
  \text{modeb}(*, \text{dec}(+\text{real},-\text{real})) \\
  \text{modeb}(*, \text{plus}(+\text{real}, +\text{real},-\text{real})) \\
  \text{determination(mult/3, mult/3)} \\
  \text{determination(mult/3, dec/2)} \\
  \text{determination(mult/3, plus/3)} \\
  \]

\[
C = \text{mult}(E,F,G) \leftarrow \text{dec}(E, H), \text{mult}(F, H, I), \text{plus}(F, I, G).
\]
Bottom–Clause

In Progol, the search space for a candidate hypothesis starts from \((h \leftarrow)\) and specializations are added in order to minimize its loss function.
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It is built from a chosen example by applying iteratively substitutions to match all possible *modeb* literals, in top–down order, according to its *modeh* definition, background knowledge and *determination* restrictions.
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- It uses a *deepness* \((d)\) input parameter, which controls the amount of cycles through *modeb* literals
In Progol, the search space for a candidate hypothesis starts from \((h ←)\) and specializations are added in order to minimize its loss function.

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It uses a *deepness* \((d)\) input parameter, which controls the amount of cycles through *modeb* literals.

After built, it is then variabilized to be used as a specialization boundary.
Example

**Input:** example: `mult(2, 4, 8)`, `maxDeepness = 1`

**Modes:**
- `modeh(*, mult(+real, +real, -real))`
- `modeb(*, dec(+real, -real))`
- `modeb(*, plus(+real, +real, -real))`

**Background Knowledge:**
- `dec(2, 4); dec(2, 5); plus(2, 2, 4); plus(2, 4, 6);`

**Possible terms to use:** ∅
**Other terms:** ∅

⊥ = ∅
**Current deepness:** 0
**Example**

**Input:** example: \text{mult}(2, 4, 8), \text{maxDeepness} = 1

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- \text{modeh}(*, \text{mult}(+\text{real}, +\text{real}, -\text{real}))
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**Background Knowledge:**
- \text{dec}(2, 4)
- \text{dec}(2, 5)
- \text{plus}(2, 2, 4)
- \text{plus}(2, 4, 6)

**Possible terms to use:** A(2), B(4)
**Other terms:** C(8)

\[ \bot = \text{mult}(A, B, C) \leftarrow \]
**Current deepness:** 0
Example

**Input:** example: mult(2, 4, 8), maxDeepness = 1

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modeh(*, mult(+real, +real, -real))
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dec(2, 4); **dec(2, 5)**; plus(2, 2, 4); plus(2, 4, 6);

**Possible terms to use:** A(2), B(4), **D(5)**
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\[
\perp = \text{mult}(A, B, C) \leftarrow \text{dec}(A, B), \text{dec}(A, D)
\]

**Current deepness:** 0
Example

Input: example: mult(2, 4, 8), maxDeepness = 1

Modes:
modeh(*, mult(+real, +real, -real))
modeb(*, dec(+real, -real))
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⊥ = mult(A, B, C) ← dec(A, B), dec(A, D), plus(A, A, B)
Current deepness: 0
Example

Input: example: \text{mult}(2, 4, 8), \text{maxDeepness} = 1

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\text{modeh}(\ast, \text{mult}(+\text{real}, +\text{real}, -\text{real}))
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Background Knowledge:
dec(2, 4); dec(2, 5); plus(2, 2, 4); \textbf{plus}(2, 4, 6);

Possible terms to use: A(2), B(4), D(5), E(6)
Output terms: C(8)

\bot = \text{mult}(A, B, C) \leftarrow \text{dec}(A, B), \text{dec}(A, D), \text{plus}(A, A, B), \textbf{plus}(A, B, E)

Current deepness: 1 (algorithm stop)
Specialization Operator

• An order on \( \perp \) is assumed and let \( \perp (k) \) be the \( k \)-th element in \( \perp \).
Specialization Operator

- An order on $\bot$ is assumed and let $\bot(k)$ be the k–th element in $\bot$
- Since $H \prec_\theta \bot$, there must be a substitution $\theta$ such that for each literal $h$ in $H$, there is a literal $l$ such that $h\theta = l$
Specialization Operator

- An order on $\bot$ is assumed and let $\bot(k)$ be the $k$–th element in $\bot$
- Since $H \prec_\theta \bot$, there must be a substitution $\theta$ such that for each literal $h$ in $H$, there is a literal $l$ such that $h\theta = l$
- The substitution operator $\delta$ can be defined as:

$$< P(v_1, \ldots, v_m, \theta_m) > \in \delta(\theta, k) \text{ if and only if}$$
- $P(u_1, \ldots, u_m)$ is the $k$–th literal in $\bot$
- $\theta_0 = \theta$
- if $v_j/u_j \in \theta_{j-1}$ then $\theta_j = \theta_{j-1}$ for $0 < j \leq m$
Specialization Operator

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  - $\theta_0 = \theta$
  - if $v_j / u_j \in \theta_{j-1}$ then $\theta_j = \theta_{j-1}$ for $0 < j \leq m$

- The specialization operator $\rho$ can be defined as:

  $\langle r', \theta', k' \rangle \in \rho(\langle r, \theta, k \rangle)$ if and only if either
  - $r' = c \cup \{l\}$, $k' = k$, $\langle l, \theta' \rangle \in \delta(\theta, k)$, $r' \in \{\text{Rulespace}\}$ or
  - $r' = c$, $k' = k + 1$, $\theta' = \theta$

  for $1 \leq k \leq |\perp|$
Specialization Choosing

From all possible substitutions using $\rho$, the one that minimizes $loss^{progol}(E, B, H)$. The search method used is A*, which tracks the best path regarding $loss^{progol}$ with a priority list for other options:

```
mult(A, B, C) ←

mult(A, B, C) ← dec(A, B)  mult(A, B, C) ← dec(A, C)
```
Outline

1. Introduction
   - Motivation
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   - Overview

2. Background Knowledge
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   - First-Order Logic
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4. Neural–Symbolic Systems
   - Introduction
   - C–IL2P
   - CILP++

5. Conclusion

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Neural–Symbolic Systems

Neural–Symbolic Integration

- **Symbolical systems**, such as Progol, holds very powerful representative power through First–Order logics briefly explaining Propositional and First–Order Logics.
Neural–Symbolic Integration

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- As seen during introduction, each one of those paradigms holds advantages and advantages, in a quite “complementary” way.
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- **Connectionistic systems**, being neural networks its main representative, have great noise–robustness capabilities and can model knowledge as probabilities through their weights
- As seen during introduction, each one of those paradigms holds advantages and advantages, in a quite “complementary” way
- Why not combine both paradigms?
Neural–Symbolic Integration

<table>
<thead>
<tr>
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<th>Symbolical</th>
<th>Connectionistic</th>
</tr>
</thead>
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<tr>
<td>Multiple Learning</td>
<td>Slow learning of multiple concepts</td>
<td>Efficient parallel learning of multiple concepts</td>
</tr>
<tr>
<td>Noise Robustness</td>
<td>Limited, artificial noise-robustness capabilities</td>
<td>Natural, method-inherent noise treatment</td>
</tr>
<tr>
<td>Concept Clarity</td>
<td>Learned concepts formally represented</td>
<td>Concepts are tangled inside numerical data</td>
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<td>Background Data</td>
<td>Makes partial or total use of background data</td>
<td>Only empirical examples are used</td>
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Idea

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Neural–Symbolic Systems  C–IL2P

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Idea

- Union two of the most popular symbolic and connectionistic representatives: ILP and Neural Networks
- Enhance their advantages, while suppressing their flaws
- A relational (recursive) three-layer network is built from a propositional logic program and it is then used to train examples
- This way, a knowledge-based neural network is created (which solves the main problem of classical neural networks) which is capable of using “almost” full capabilities of back-propagation training regarding noise robustness and incomplete data (which are the two main ILP weakpoints)
C–IL2P Knowledge Flow

System Building

Net Training

Testing/Inference

Know. Extract.

Manoel França (City University)
C–IL2P Structure

\[ B = \{ A \leftarrow B, C; B \leftarrow C, \text{not } D, E; D \leftarrow E \} \]

\[ \text{(1)} \quad \text{(2)} \quad \text{(3)} \]

\[
\begin{array}{c}
\text{N} \\
\text{Outputs} \\
A & B & D \\
\text{1.0} \\
B & C & D & E \\
\text{1.0} \\
\text{Inputs} \\
\end{array}
\]
Applications

As expected of a hybrid system, C–IL2P can be used in any problem in which any one of its components would be eligible to be applied.
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- Additionally (as the knowledge flow has shown before), the way C–IL2P deals with information processing can allow it to be applied in some unique applications, such as fault diagnosis and multi–instance learning problems.
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- Additionally (as the knowledge flow has shown before), the way C–IL2P deals with information processing can allow it to be applied in some unique applications, such as fault diagnosis and multi-instance learning problems.

- If extended to work with First–Order logic programs, its applicability would be hugely enhanced.
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Main Concepts

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  - Applying the language bias on the building step of C–IL2P.
Main Concepts

- CILP++ is the results of my work on C–IL2P to allow it to work with First–Order logics
- Different ways of using First–Order logics are being studied:
  - Using Bottom–Clauses as examples;
  - Different kinds of propositionalizations;
  - Applying the language bias on the building step of C–IL2P
- It uses the same building process of C–IL2P, but differs in the network training, depending on the kind of First–Order information that is being given to it
What Has Been Done

- Enhancements in the underlying neural network to optimize it
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- Testings using *Bottom–Clauses* and RSA propositionalization
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- Testings using *Bottom–Clauses* and RSA propositionalization
- A friendly GUI using *wxWidgets* to let other people uses the basic C–IL2P functionality (an open–source C–IL2P project is already active at SourceForge: http://sourceforge.net/projects/cil2p/)
What Will Be Done

In priority order:

- Fine-tuning the system to work with bottom-clauses and propositionalized datasets
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- Fine-tuning the system to work with bottom-clauses and propositionalized datasets
- Study how knowledge extraction will take place in this new system
- Test other ways of using First-Order logics into C–IL2P without major structural changes
- Analyze structural changes on CILP++ to allow better suitability for First–Order logic processing
Applications

CILP++, working with First-Order logics, will be able to completely explore domain-theory and classification problems. It will be the first hybrid system to achieve that.
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  - Web-semantics
  - Intelligent Agents
Connectionism and symbolism are two paradigms that were kept separated for a long time, but this is coming to an end.
Final Remarks

- Connectionism and symbolism are two paradigms that were kept separated for a long time, but this is coming to an end.
- Symbolism, supported by its very successful machine learning algorithm called ILP, is a necessary tool to express knowledge in a formal and clear way and to represent complex and hierarchical relations.
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Symbolism, supported by its very successful machine learning algorithm called ILP, is a necessary tool to express knowledge in a formal and clear way and to represent complex and hierarchical relations.

Neural–Symbolic Integration is one way–to–go in going one step further in learning, reasoning and expressing knowledge.
Recommended Reading

Recommended Reading

Recommended Reading

Recommended Reading

Thank You!

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