Abduction and Induction through Inverse Entailment and Consequence Finding

Katsumi Inoue

National Institute of Informatics, Japan

AIAI'05 Edinburgh, July 29, 2005

Consequence Finding

- Given an axiom set, the task of <u>consequence finding</u> or <u>theorem finding</u> is to find out some theorems of interest [Lee, 1967].
- Theorems to find out are not given in an explicit way, but are characterized by some properties.
- Task is clearly distinguished from <u>proof finding</u> or <u>theorem proving</u>. However, theorem proving is a special case of consequence finding.
- Consequence finding is a part of deduction, but can be used for abduction and induction.

Abduction and Induction: Logical Framework

Input:

- *B* : background theory
- *E*: (positive) examples ∠observations

Output:

• *H* : hypothesis satisfying that

 $\blacksquare B \land H \vDash E$

B \wedge *H* is consistent.

Abduction and Induction: Logical Framework

$$\blacksquare B \land H \vDash E$$

- \blacksquare *B* \land *H* is consistent.
- The logical framework is exactly the same.
- A different formalism exists for induction, e.g., *descriptive induction*, but can be unified with the above framework [Inoue & Saito, ILP'04].
- Induction often gets negative examples, but abduction can be extended too [Inoue & Sakama, IJCAI-95].
 - Theoretical results for one can be easily transferred to the other. E.g., The notion of **equivalence** is explored for abduction [Inoue & Sakama, MBR'04; IJCAI-05] and for induction [Sakama & Inoue, ILP'05].
 - Computation can also be unified.

Inverse Entailment

Given that

$$B \wedge H \models E$$
,

computing a hypothesis *H* can be done by

$$B \wedge \neg E \models \neg H$$
.

I.e., $\neg H$ deductively follows from $B \land \neg E$.

Inverse Entailment

B:Human(Socrates),E:Mortal(Socrates),H: $\forall x \ (Human(x) \supset Mortal(x))$ satisfies that:

$$B \wedge H \models E$$

In fact,

 $B \wedge \neg E = Human(Socrates) \wedge \neg Mortal(Socrates)$ $\models \exists x (Human(x) \wedge \neg Mortal(x)) = \neg H.$

IE for Abduction [Inoue, 1992]

$B \land \neg E \models \neg H$

Computation through *consequence finding*

- *E* : conjunction of (existentially-quantified) **literals**
- *H* : conjunctions of **literals**
- *B*: (full) clausal theory (**non-Horn** clauses)
- Note: Both $\neg E$ and $\neg H$ are **clauses**.
- sound and complete

<u>SOLAR</u>

[Nabeshima, Iwanuma & Inoue, 2003]

- <u>Input</u>: (1) the set of input clauses (TPTP library format), (2) the top clause, (3) the production field, and (4) the search strategy.
- For example, the graph completion problem (find an arc which enables a path from a to d) is described as follows:

b

SOLAR outputs four consequences: [-arc(a, d)]

```
[-arc(a, c)]
```

```
[-arc(b, d)]
```

```
[-arc(b, c)]
```

IE for ILP [Muggleton, 1995]

$B \land \neg E \models \neg H$

- Use consequence-finding procedures twice [Yamamoto 1997]
- *B* : Horn clausal theory
- *E* : single Horn clause
- H: single (non-)Horn clause
- Note: Neither ¬E nor ¬H is a single clause, and both contain existentially quantified variables.

IE with ⊥-clause: Incompleteness

<u>Approach</u>: Compute the *L*-clause:

 $\perp (B, E) = \{ \neg L \mid L \text{ is a literal s.t. } B \land \neg E \models L \}.$

Hypothesis *H* is constructed by generalizing \bot -clause:

 $H \models \bot (B, E)$.

- Sound but incomplete for recursive clauses [Yamamoto, 1997]
- Sufficient conditions for completeness
 [Furukawa et al., 1997; Yamamoto, 1997;1999]
 - Incompleteness due to single-clause hypotheses [Ray, 2003]

Complete Calculus for IE

$$B \land \neg E \models \neg H$$

CF-Induction [Inoue, 2001]

- Compute the *characteristic clauses* of $B \land \neg E$
- Use any *consequence-finding* procedure.
- Use any *generalizer*.
- Includes the bottom method and abductive computation.
- B: full clausal theory (non-Horn clauses)
- *E* : full clausal theory (non-Horn clauses)
- H: full clausal theory (non-Horn clauses)
- Sound and complete

CF-Induction: Principle

$B \land H \models E$ $\Leftrightarrow B \land \neg E \models \neg H$ $\Leftrightarrow B \land \neg E \models Carc(B \land \neg E, P) \models CC(B, E) \models \neg H$ $\Leftrightarrow CC(B, E) \subseteq Carc(B \land \neg E, P),$

 $\neg CC(B,E) \equiv F, \quad H \models F$ (where F is CNF)

CF-Induction: Algorithm

- 1. Compute *Carc(B*∧ ¬*E*, *P*).
- 2. Construct *CC(B,E)* such that
 - $\square CC(B,E) \subseteq Carc(B \land \neg E, P);$
 - $CC(B,E) \cap NewCarc(B, \neg E, P) \neq \phi$.
- **3**. Convert $\neg CC(B,E)$ into CNF F.
- 4. Generalize F to H such that

 $\blacksquare B \land H \text{ is consistent.}$

CF-Induction: Generalizers

Given a CNF formula *F*, find a CNF formula *H* such that

 $H \models F$.

- inverse Skolemization
- anti-instantiation
- anti-subsumption (dropping literals from clauses)
- anti-weakening (addition of clauses)
- inverse resolution
- Plotkin's least generalization

CF-Induction: Buntine's Example

B: $cat(x) \supset pet(x)$, $small(x) \land fluffy(x) \land pet(x) \supset cuddly_pet(x)$. E: $fluffy(x) \land cat(x) \supset cuddly_pet(x)$.

NewCarc(B, $\neg E$, **P**): fluffy(s_x), cat(s_x), \neg cuddly_pet(s_x), pet(s_x), \neg small(s_x)

 $CC(B, E) = NewCarc(B, \neg E, P)$

H: $fluffy(x) \land cat(x) \land pet(x) \supset cuddly_pet(x) \lor small(x)$

CF-Induction: Yamamoto's Example

B: even(0), $odd(x) \supset even(s(x))$. **E**: odd(s(s(s(0)))).

NewCarc(B, $\neg E$, P): $\neg odd(s(s(s(0))))$.

CC(B,E): even(0), $odd(s(0)) \supset even(s(s(0)))$, $\neg odd(s(s(s(0))))$.

CNF(¬*CC(B,E)***)**:

 $even(0) \supset odd(s(0)) \lor odd(s(s(s(0)))),$ $even(0) \land even(s(s(0))) \supset odd(s(s(s(0)))).$

H: $even(x) \supset odd(s(x))$.

Yamamoto & Fronhőfer's Example

B: $dog(x) \land small(x) \supset pet(x)$. **E**: pet(c).

 $NewCarc(B, \neg E, \mathbf{P}): \neg pet(c), \neg dog(c) \lor \neg small(c).$ $CC(B, E) = NewCarc(B, \neg E, \mathbf{P}).$

 $\neg CC(B,E)$: pet(c) V (dog(c) \land small(c)).

CNF(\neg *CC(B,E)***)**: *pet(c)* V *dog(c)*, *pet(c)* V *small(c)*.

H: $pet(x) \lor dog(x)$, $pet(x) \lor small(x)$.

Abduction and Induction in Network Inference





S1

