Logic Learning for Multi Agent Systems
ACAI-2019

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`http://cer.iit.demokritos.gr`

Presenter: Nikos Katzouris

Overview

- Part I: Dealing with Interacting Entities in Dynamic Domains.
  - Norm-governed systems.
  - Complex Event Recognition systems.
  - Logical specifications of domain dynamics.
  - The Event Calculus.
- Part II: Learning logical specifications of domain dynamics.
  - Basics of Logical & Relational Learning.
  - Learning with the Event Calculus.
  - Abductive-Inductive learning.
  - Learning from relational data streams.
- Part IV: Statistical Relational Learning.
  - Markov Logic Networks.
  - Online structure & weight learning.

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Dealing with Interacting Entities in Dynamic Domains

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Electronic markets

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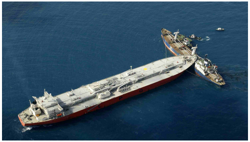
Agent-based modeling



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Intelligent monitoring & complex event detection

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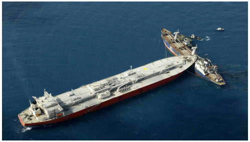

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Intelligent monitoring & complex event detection

- Requirements:
  - Specifying & enforcing norms on entities' interactions.
  - Handling time & change.
    - Dealing with the effects of agent actions/event occurrences.
  - Verifying, tracing and explaining behavior.
  - Preventing failure & undesired behavior.

Example: Norm-governed Systems

- Pick a network:
  - individual people, forming online communities or social networks via computer-mediated communication
  - computing devices, forming ad hoc networks, Sensor Networks, etc.
  - business processes, forming virtual enterprises/organizations, computational economies, etc.
- Open systems:
  - autonomous components of heterogeneous provenance
  - can assume that components can communicate (i.e. a common language)
  - can *not* assume a common objective or central controller

Example: Norm-governed Systems

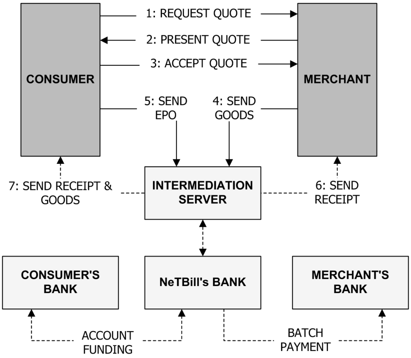
- Common features of open systems:
  - Dynamic and ‘volatile’: the environment, network topology and constituent nodes can vary rapidly and unpredictably
  - ‘Evolutionary’: known nodes can come/go, but can also have new nodes and node ‘death’
  - Co-dependence and internal competition: nodes need others to satisfy their own requirements, but may also behave to maximise individual (rather than collective) utility
  - Partial knowledge: no single source knowledge, union of knowledge may be inconsistent
  - Sub-ideal operation: the nodes may fail to comply according to the system specification, by accident, necessity, or design.

Example: Norm-governed Systems

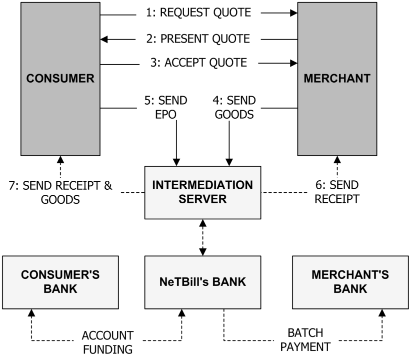
Addressing the features:

- Specify obligations and permissions, and describe agent behaviour as governed by norms, which may be violated, accidentally or on purpose.
- Predict, test, and verify the properties that hold if these norms are violated, and test the effectiveness of introducing proposed control, enforcement, and recovery mechanisms.
- Specify rules and procedures for adapting to changing environmental, financial and social conditions.

Example: Norm-governed Systems

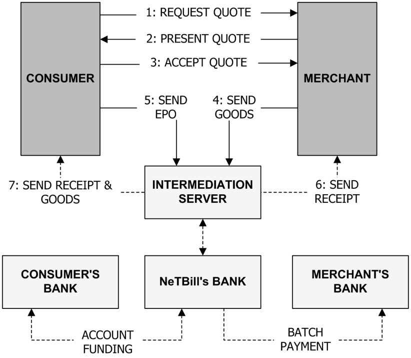


Example: Norm-governed Systems



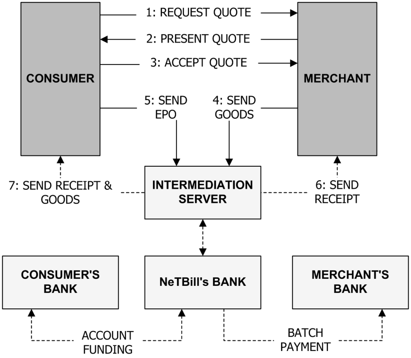
- Effects of actions.
  - A request is pending for as long as it has been issued by the consumer and has not been presented by the merchant.

Example: Norm-governed Systems



- Effects of actions.
  - A request is pending for as long as it has been issued by a consumer and has not been presented by the merchant.
  - $action_1 \rightarrow effect \xrightarrow{\text{holds until}} action_2$

Example: Norm-governed Systems



- Norms: Institutional power
  - A consumer is empowered to accept a quote if that quote was issued by a merchant, and the quote has not expired.

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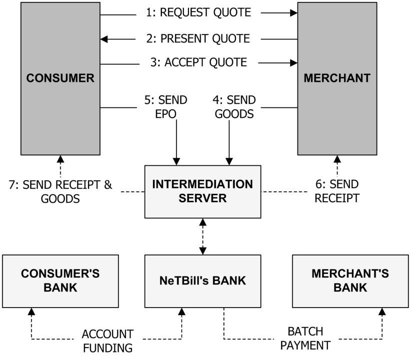
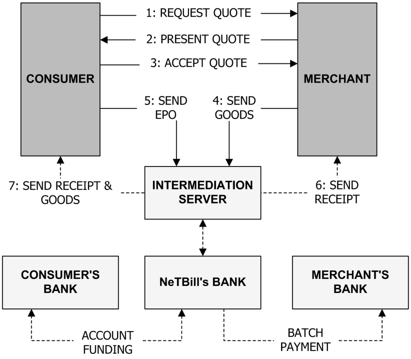


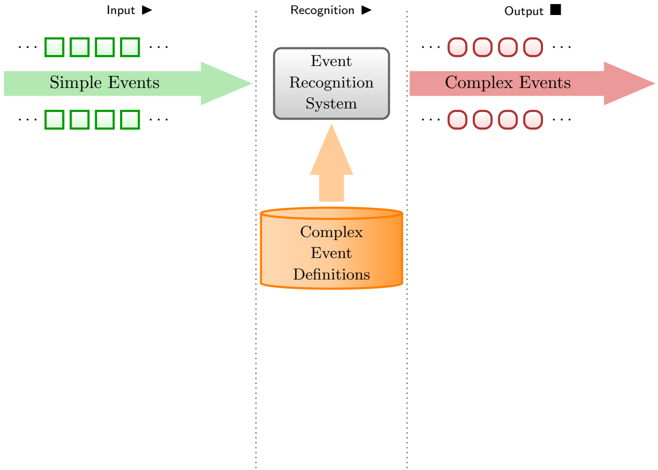
- Norms: Institutional power
  - A consumer is empowered to accept a quote for as long as that quote has been issued by a merchant, and the quote has not expired .
  - $\mathit{action}_1 \rightarrow \mathit{effect} \xrightarrow{\text{holds until}} \mathit{event\ occurrence}$

Example: Norm-governed Systems



- Norms: Obligation
  - A consumer is obliged to pay the agreed price to the contracting merchant by a specified deadline for as long as the consumer has accepted the quote, while being empowered to do so, and has not yet payed.
  - Similar durative cause-effect structure as before.

Example: Complex Event Recognition Systems



Example: Complex Event Recognition Systems

Maritime Surveillance

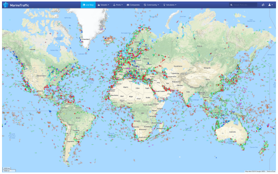
Input ▶ | Recognition ▶ | Output ■

Simple Events

Event Recognition System

Complex Event Definitions

Complex Events



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AIS signals

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Suspicious vessel rendezvous

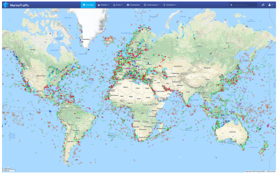
Example: Complex Event Recognition Systems

Maritime Surveillance

Input ▶ | Recognition ▶ | Output ■

Simple Events → Event Recognition System → Complex Events

Complex Event Definitions



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Suspicious vessel rendezvous

Two vessels are in suspicious rendezvous for as long as one sails close to another in the open sea and none sails away.

Example: Complex Event Recognition Systems

Maritime Surveillance

Input ▶ Recognition ▶ Output ■

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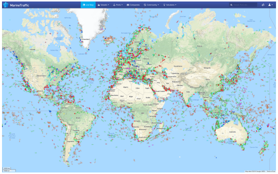
Event Recognition System

Complex Events



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Complex Event Definitions

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Suspicious vessel rendezvous

Two vessels are in suspicious rendezvous for as long as one sails close to another in the open sea and none sails away .

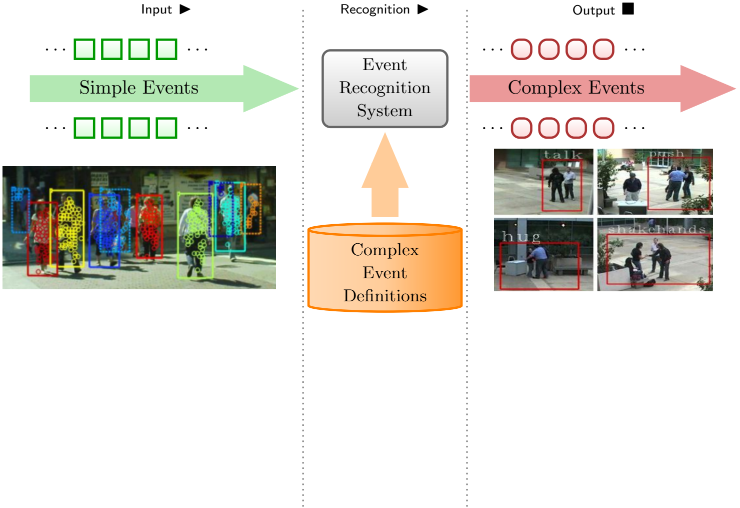
$$\textit{simple\_event\_occurrence}_1 \rightarrow \textit{effect}/\textit{complex\_event} \xrightarrow{\text{holds until}} \textit{simple\_event\_occurrence}_2$$

Example: Complex Event Recognition Systems

Maritime video

Example: Complex Event Recognition Systems

Actitivy recognition



Example: Complex Event Recognition Systems

Activity Recognition video.

Logical Specifications of Domain Dynamics

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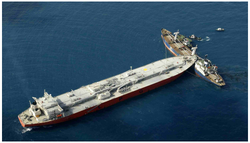

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Intelligent monitoring & complex event detection

- First-Order Logic (FOL):
  - Connections to action languages
    - Handling time & change.
  - Relational representations
    - Useful for dealing with multiple interacting entities.
  - Formal semantics
    - Useful for verifying, tracing & explaining behavior.
  - Allows arbitrarily complex background knowledge
  - Declarative, focus on what should a system do, not on how to do it.

Handling Time & Change

- Action languages:
  - representation of the agents' actions and their effects
  - exhibit a formal semantics
  - exhibit a declarative semantics
  - have direct routes to (efficient) implementation
- Examples:
  - Situation Calculus
  - Event Calculus
  - $C+$
- We will use the Event Calculus

The Event Calculus

- General purpose language for representing events, and for reasoning about effects of events.
- An action language with a logical semantics. Therefore, there are links to:
  - Implementation directly in Prolog.
  - Implementation in other programming languages.
- Prolog:
  - specification is its own implementation;
  - hence executable specification.
- We will use the Event Calculus for Run-Time reasoning (RTEC):
  - Highly efficient;
  - Sufficiently expressive.

Fluents and Events

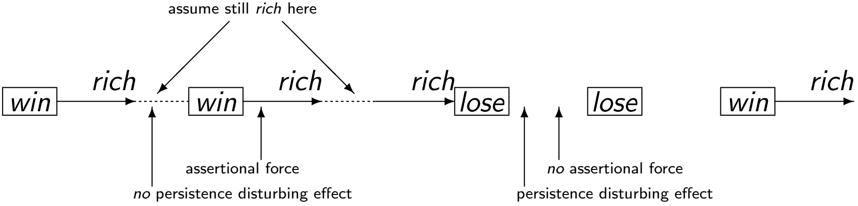
- Focus on events rather than situations; local states rather than global states
- Fluents
  - A fluent is a proposition whose value changes over time
  - A local state is a period of time during which a fluent holds continuously
- Events
  - *initiate* and *terminate* ...
  - ... a period of time during which a fluent holds continuously
- Example
  - $give(X, obj, Y)$ initiates $has(Y, obj)$
  - $give(X, obj, Y)$ terminates $has(X, obj)$

Event Calculus

- Fluents:
  - Values are assigned initially
  - Values are given when asserted (initiated)
  - Values persist until disturbed (terminated)
  - Otherwise we have ‘missing information’
- A formula of the form
  - *Event* terminates *fluent*
  - Has persistence disturbing effect, but no assertional force
- A formula of the form
  - *Event* initiates *fluent*
  - Has assertional force, but no persistence disturbing effect

Example

- $win\_lottery(X)$ initiates $rich(X)$
  - Winning the lottery initiates rich (but you might be rich already)
- $lose\_wallet(X)$ terminates $rich(X)$
  - Losing your wallet terminates rich (but you might not be rich when you lose it)



Event Calculus

- Actual syntax:

$$\textbf{initiatedAt}(\mathit{rich}(X) = \text{true},\ T) \leftarrow \\ \quad \textbf{happensAt}(\mathit{win\_lottery}(X),\ T)$$

$$\textbf{terminatedAt}(\mathit{rich}(X) = \text{true},\ T) \leftarrow \\ \quad \textbf{happensAt}(\mathit{lose\_wallet}(X),\ T)$$

- Given rules of the above form, the Event Calculus computes the maximal intervals for which a fluent has some value continuously. Eg:

  $\textbf{holdsFor}(\mathit{rich}(X) = \text{true},\ I)$

  where $I = [(S_1, E_1), \ldots, (S_n, E_n)]$

- Also: $\textbf{holdsAt}(\mathit{rich}(X) = \text{true},\ T)$ iff T in the list I of maximal intervals.

Event Calculus

- Sometimes it is easier to write the conditions in which a fluent has some value:

$$\begin{aligned}&\mathbf{holdsFor}(\mathit{happy}(X) = \mathsf{true},\ I) \leftarrow \\ &\qquad \mathbf{holdsFor}(\mathit{rich}(X) = \mathsf{true},\ I_1), \\ &\qquad \mathbf{holdsFor}(\mathit{loc}(X) = \mathit{pub},\ I_2), \\ &\qquad \mathbf{union\_all}([I_1, I_2],\ I)\end{aligned}$$

- How would you write the above rule in terms of **initiatedAt** and **terminatedAt**?

Event Calculus

- Short version:

$$\begin{aligned}&\textbf{holdsFor}(\mathit{happy}(X) = \mathsf{true},\ I) \leftarrow\\&\qquad \textbf{holdsFor}(\mathit{rich}(X) = \mathsf{true},\ I_1),\\&\qquad \textbf{holdsFor}(\mathit{loc}(X) = \mathit{pub},\ I_2),\\&\qquad \textbf{union\_all}([I_1, I_2],\ I)\end{aligned}$$

- Long version:

$$\begin{aligned}&\textbf{initiatedAt}(\mathit{happy}(X) = \mathsf{true},\ T) \leftarrow\\&\qquad \textbf{initiatedAt}(\mathit{rich}(X) = \mathsf{true},\ T)\end{aligned}$$

$$\begin{aligned}&\textbf{initiatedAt}(\mathit{happy}(X) = \mathsf{true},\ T) \leftarrow\\&\qquad \textbf{initiatedAt}(\mathit{loc}(X) = \mathit{pub},\ T)\end{aligned}$$

$$\begin{aligned}&\textbf{terminatedAt}(\mathit{happy}(X) = \mathsf{true},\ T) \leftarrow\\&\qquad \textbf{terminatedAt}(\mathit{rich}(X) = \mathsf{true},\ T),\\&\qquad \text{not } \textbf{holdsAt}(\mathit{loc}(X) = \mathit{pub},\ T)\end{aligned}$$

$$\begin{aligned}&\textbf{terminatedAt}(\mathit{happy}(X) = \mathsf{true},\ T) \leftarrow\\&\qquad \textbf{terminatedAt}(\mathit{loc}(X) = \mathit{pub},\ T),\\&\qquad \text{not } \textbf{holdsAt}(\mathit{rich}(X) = \mathsf{true},\ T)\end{aligned}$$

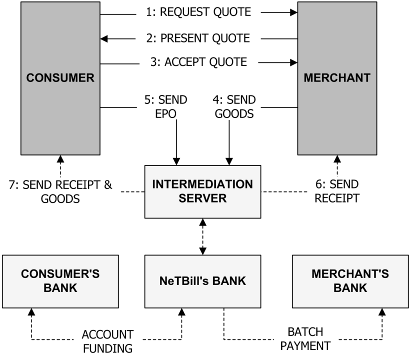
General Formulation

Predicate	Meaning
happensAt$(E,\ T)$	Event E is occurring at time T
initially$(F = V)$	The value of fluent F is V at time 0
initiatedAt$(F = V,\ T)$	At time T a period of time for which $F = V$ is initiated
terminatedAt$(F = V, T)$	At time T a period of time for which $F = V$ is terminated
holdsFor$(F = V,\ I)$	I is the list of the maximal intervals for which $F = V$ holds continuously
holdsAt$(F = V,\ T)$	The value of fluent F is V at time T

General Formulation (Interval Manipulation)

Predicate	Meaning
union_all$(L,\ I)$	I is the list of maximal intervals produced by the union of the lists of maximal intervals of list L
intersect_all$(L,\ I)$	I is the list of maximal intervals produced by the intersection of the lists of maximal intervals of list L
relative_complement_all$(I',\ L,\ I)$	I is the list of maximal intervals produced by the relative complement of the list of maximal intervals I' with respect to every list of maximal intervals of list L

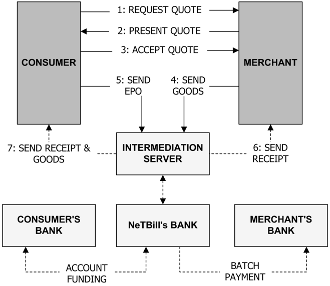
Examples Revisited



- A consumer is empowered to accept a quote for as long as that quote has been issued by a merchant, and the quote has not expired .

$$
\begin{aligned}
&\textbf{holdsFor}(\mathit{pow}(C, \mathit{accept\_quote}(C, M)) = \mathrm{true},\ I) \leftarrow \\
&\quad \textbf{holdsFor}(\mathit{role\_of}(C, \mathit{consumer}) = \mathrm{true},\ I_1), \\
&\quad \textbf{holdsFor}(\mathit{role\_of}(M, \mathit{merchant}) = \mathrm{true},\ I_2), \\
&\quad \textbf{holdsFor}(\mathit{quote}(M, C) = \mathrm{true},\ I_3), \\
&\quad \textbf{intersect\_all}([I_1, I_2, I_3],\ I)
\end{aligned}
$$

Examples Revisited



- A consumer is obliged to pay the agreed price to the contracting merchant by a specified deadline for as long as the consumer has accepted the quote, while being empowered to do so, and has not yet payed.

$$
\begin{aligned}
&\mathbf{initiatedAt}(obl(C, send\_EPO(C, IS)) = \text{true},\ \ T\ ) \leftarrow \\
&\quad \mathbf{happensAt}(accept\_quote(C, M),\ \ T), \\
&\quad \mathbf{holdsAt}(pow(C, accept\_quote(C, M)) = \text{true},\ \ T), \\
&\quad \mathbf{holdsAt}(role\_of(IS, iServer) = \text{true},\ \ T)
\end{aligned}
$$

$$
\begin{aligned}
&\mathbf{terminatedAt}(obl(C, send\_EPO(C, IS)) = \text{true},\ \ T) \leftarrow \\
&\quad \mathbf{happensAt}(send\_EPO(C, IS),\ \ T)
\end{aligned}
$$

Examples Revisited

Event Calculus as a Reasoning Engine

holdsAt$(F, T+1) \leftarrow$
  initiatedAt$F, T)$

holdsAtAt$(F, T+1) \leftarrow$
  holdsAt(F, T),
  not terminatedAt(F, T).

Very efficient inference: *Artikis et al. An Event Calculus for Event Recognition, TKDE, 2015.*

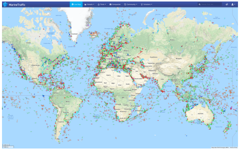
Input ▶ Recognition ▶ Output ■

Simple Events

Event Recognition System

Complex Events

Complex Event Definitions



AIS signals,
contextual info (ports, weather, environment...)

holdsAt$(rendezVous(vessel_1, vessel_2), 10)$
holdsAt$(rendezVous(vessel_1, vessel_2), 11)$
holdsAt$(rendezVous(vessel_1, vessel_2), 12)$
...

initiatedAt$(rendezVous(X, Y), T) \leftarrow$
  happensAt$(stopped(X), T)$,
  happensAt$(lowSpeed(Y), T)$,
  $farFromPorts(X, T)$,
  $farFromPorts(Y, T)$,
  $closeProximity(X, Y, T)$.

terminatedAt$(rendezVous(X, Y), T) \leftarrow$
  happensAt$(travelSpeed(X), T)$,
  $not\ closeProximity(X, Y, T)$.

Examples Revisited

Event Calculus as a Reasoning Engine

holdsAt(F, $T+1$) ←
initiatedAtF, T)

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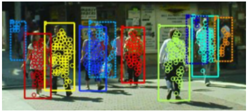
Input ▶ | Recognition ▶ | Output ■

Simple Events → Event Recognition System → Complex Events

Complex Event Definitions



happensAt($active(id_0)$, 10)
holdsAt($coord(id_0, 20.88, 11.90)$, 10)
happensAt($active(id_1)$, 10)
holdsAt($coord(id_1, 22.34, 15.23)$, 10)
...

holdsAt($meet(id_0, id_1)$, 11)
holdsAt($meet(id_0, id_1)$, 12)
holdsAt($meet(id_0, id_1)$, 13)
...

initiatedAt($meet(X, Y)$, T) ←
happensAt($active(X)$, T),
happensAt($active(Y)$, T),
holdsAt($close(X, Y, 25)$, T).

terminatedAt($meet(X, Y)$, T) ←
happensAt($walking(X)$, T),
not holdsAt($close(X, Y, 25)$, T).

Summary: So far

- Introduced the Event Calculus
  - Events and Fluents.
  - Fluent formulations.
- Formulating domain dynamics specifications in the Event Calculus.
- Next: Learning such specifications from data.

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Learning Logical Specifications of Domain Dynamics

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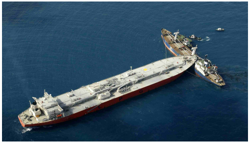

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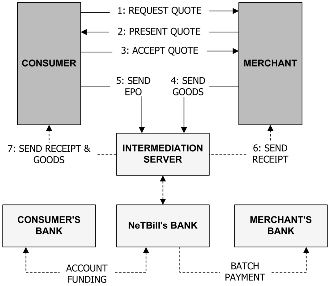
Intelligent monitoring & complex event detection

- Goal:
  - Given traces of a system's/domain's execution/evolution in time.
  - Learn the rules that govern the dynamics of the system/domain.

Learning Logical Specifications of Domain Dynamics



- Given past examples of transactions.
- Learn the underlying normative temporal rules.

$$\begin{aligned}
&\mathbf{initiatedAt}(\mathit{obl}(C, \mathit{send_EPO}(C, \mathit{IS})) = \text{true},\ \ T\ ) \leftarrow\\
&\quad \mathbf{happensAt}(\mathit{accept_quote}(C, M),\ \ T),\\
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\end{aligned}$$

$$\begin{aligned}
&\mathbf{terminatedAt}(\mathit{obl}(C, \mathit{send_EPO}(C, \mathit{IS})) = \text{true},\ \ T) \leftarrow\\
&\quad \mathbf{happensAt}(\mathit{send_EPO}(C, \mathit{IS}),\ \ T)
\end{aligned}$$

Learning Logical Specifications of Domain Dynamics

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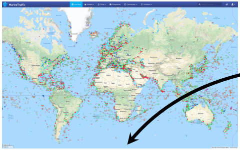
Simple Events → Event Recognition System → Complex Events



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contextual info (ports, weather, environment...)

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Learn this

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From These

Learning Logical Specifications of Domain Dynamics

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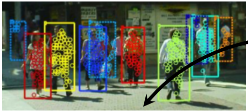


happensAt($active(id_0)$, 10)
holdsAt($coord(id_0, 20.88, 11.90)$, 10)
happensAt($active(id_1)$, 10)
holdsAt($coord(id_1, 22.34, 15.23)$, 10)
...

holdsAt($meet(id_0, id_1)$, 11)
holdsAt($meet(id_0, id_1)$, 12)
holdsAt($meet(id_0, id_1)$, 13)
...

Learn this

initiatedAt($meet(X, Y)$, T) $\leftarrow$
    happensAt($active(X)$, T),
    happensAt($active(Y)$, T),
    holdsAt($close(X, Y, 25)$, T).

terminatedAt($meet(X, Y)$, T) $\leftarrow$
    happensAt($walking(X)$, T),
    not holdsAt($close(X, Y, 25)$, T).

From These

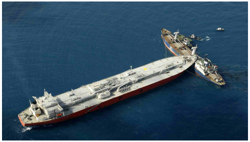
Learning Logical Specifications of Domain Dynamics

kdnuggets.com

Electronic markets

www.bankofengland.co.uk

Agent-based modeling



cer.iit.demokritos.gr

Intelligent monitoring & complex event detection

- Why?
  - The specifications may not always be known in advance.
  - Even if they are, manual authoring is time-consuming & error-prone.
  - The specifications are not static in principle.
    - They often change over time reflecting change in the domain.
    - Manual "tweaking" towards retaining performance is hard.
  - A learnt model can fit data properties that a human cannot foresee.
    - It is therefore likely to be more robust.
    - An initial, hand-crafted set of specifications may be improved by learning.

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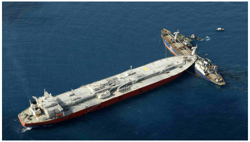

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Intelligent monitoring & complex event detection

- How?
  - Logic-based approaches offer direct connections to machine learning
    - Inductive Logic Programming (ILP).
    - Statistical Relational Learning.
  - Arbitrarily complex background knowledge easy to incorporate into the learning task.
  - Interpretable models.

Overview

- Part I: Dealing with Interacting Entities in Dynamic Domains.
  - Norm-governed systems.
  - Complex Event Recognition systems.
  - Logical specifications of domain dynamics.
  - The Event Calculus.
- Part II: Learning logical specifications of domain dynamics.
  - Basics of Logical & Relational Learning (ILP).
  - Then: Learning with the Event Calculus.
  - Abductive-Inductive learning.
  - Learning from relational data streams.
- Part IV: Statistical Relational Learning.
  - Markov Logic Networks.
  - Online structure & weight learning.

Inductive Logic Programming (ILP)

Deduction

$\forall x(man(x) \rightarrow mortal(x))$ $\qquad$ $man(socrates).$

$$mortal(socrates).$$

Slide adapted from Zelezny et al., *Taming the Complexity of Inductive Logic Programming*, SOFSEM 2010.

Inductive Logic Programming (ILP)

Induction

General $\qquad \forall x(man(x) \rightarrow mortal(x)) \qquad man(socrates).$

Specific $\qquad mortal(socrates).$

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Induction = Generalization (logic) + Justification (statistics)

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ILP: A Very Simple Example

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bird(sparrow). bird(eagle).
plane(boeing). plane(airbus).
penguin(joe).
flies(sparrow). flies(airbus). flies(boeing). flies(eagle). not flies(joe).
entity(X) ← bird(X).
entity(X) ← plane(X).
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Find the simplest hypothesis consistent with the data, specifying when things fly.

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- No good, entails all of the given facts for flying, but it also entails `flies(joe)` which is false.

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- OK!

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```
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```

- OK!

- Simplicity $\Leftrightarrow$ over-fitting avoidance ("Occam's razor")

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- Training data, positive & negative examples E^+, E^-.
  - E.g. traces of system execution/domain evolution in time, in the form of sets of logical atoms.

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  - Simplify learning, avoid learning known stuff from scratch.
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  - E.g. a hyp. should cover all positives, no negatives.
  - ...or, as many pos. & as few negs as possible (more realistic).
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Find:

- A hypothesis $H \in \mathcal{L}$ which H is optimal according to Q.
- ...or, at least a "good-enough" $H \in \mathcal{L}$.
  - (finding an optimal H is intractable in principle).

Examples & Background Knowledge
1st Set-up: Learning from Entailment

```
bird(sparrow). bird(eagle).
plane(boeing). plane(airbus).
penguin(joe).
flies(sparrow). flies(airbus). flies(boeing). flies(eagle). not flies(joe).
entity(X) ← bird(X).
entity(X) ← plane(X).
bird(X) ← penguin(X).
```

- Positive and negative examples are target concept instances.
- Everything else is background knowledge.
- This is the classical ILP setting.

Examples & Background Knowledge
2nd Set-up: Learning from Interpretations

$I_1 = \{\texttt{bird(sparrow)}, \texttt{flies(sparrow)}\}$, $I_2 = \{\texttt{bird(eagle)}, \texttt{flies(eagle)}\}$
$I_3 = \{\texttt{plane(boeing)}, \texttt{flies(boeing)}\}$, $I_4 = \{\texttt{plane(airbus)}, \texttt{flies(airbus)}\}$,
$I_5 = \{\texttt{penguin(joe)}, \texttt{not flies(joe)}\}$
$\texttt{entity(X)} \leftarrow \texttt{bird(X)}.$
$\texttt{entity(X)} \leftarrow \texttt{plane(X)}.$
$\texttt{bird(X)} \leftarrow \texttt{penguin(X)}.$

- Examples = interpretations = sets of true facts.
- Each interpretation contains a **full description** of the example.
  - **CWA assumed within the interpretation**.
    - So, e.g. I_5 is actually simply $\{\texttt{penguin(joe)}\}$.
- All information that intuitively belongs to the example, is represented in the example, not in the background knowledge.
- Background knowledge = domain knowledge.
  - General info concerning the domain, not specific examples.

Examples & Background Knowledge
2nd Set-up: Learning from Interpretations

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- All information that intuitively belongs to the example, is represented in the example, not in the background knowledge.
- Background knowledge = domain knowledge.
  - General info concerning the domain, not specific examples.
- More efficient than Learning from Entailment.
- But also weaker, cannot learn recursive concepts, nor relations between examples.

Hypothesis Language

```
bird(sparrow). bird(eagle).
plane(boeing). plane(airbus).
penguin(joe).
flies(sparrow). flies(airbus). flies(boeing). flies(eagle). not flies(joe).
entity(X) ← bird(X).
entity(X) ← plane(X).
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```

- Syntactic constraints on the acceptable hypotheses.
- Avoid constructing hypotheses that *we know* are useless for the current task.
  - `flies(X) ← bird(X).` potentially useful.
  - `plane(X) ← bird(X).` useless.

Hypothesis Language

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- Syntactic constraints on the acceptable hypotheses.
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  - `flies(X) ← bird(X).` potentially useful.
  - `plane(X) ← bird(X).` useless.
- Mode declarations: Declarative directives for rule generation.
  - E.g. `head(flies(entity)). body(not penguin(entity)).`
  - Can be used to generate e.g. `flies(X) ← not penguin(X)` $\wedge$ `entity(X).`
  - Also, directives on how to variabilize rules, variable chaining, types of variables etc.

Learning & Search

- **Ideal:** Find the simplest theory in the given language $\mathcal{L}$ that along with the background knowledge B covers as many positives and as few negatives as possible.

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- Intractable: full search in space of theories generated by $\mathcal{L}$.
  - Doubly exponential in the size of $\mathcal{L}$.

Learning & Search

- **Ideal:** Find the simplest theory in the given language $\mathcal{L}$ that along with the background knowledge B covers as many positives and as few negatives as possible.
- Intractable: full search in space of theories generated by $\mathcal{L}$.
  - Doubly exponential in the size of $\mathcal{L}$.
- Typical ILP approaches:
  - Incremental rule learning strategies.
    - iteratively learn one "good" rule at a time until stopping criterion met.
    - Collection of such good rules approximates the learning objective.
  - Heuristic search strategies for learning a single rule.
    - Learning "the best possible" rule is also intractable.
    - Exponential search space (subsets of possible attributes).

The Set-Cover Loop

$\{\texttt{bird(sparrow)}, \texttt{flies(sparrow)}\}$
$\{\texttt{bird(eagle)}, \texttt{flies(eagle)}\}$
$\{\texttt{plane(boeing)}, \texttt{flies(boeing)}\}$
$\{\texttt{plane(airbus)}, \texttt{flies(airbus)}\}$
$\{\texttt{penguin(joe)}, \texttt{not flies(joe)}\}$

Learnt Theory:

The Set-Cover Loop

1. Select positive example.

{bird(sparrow), flies(sparrow)}
{bird(eagle), flies(eagle)}
{plane(boeing), flies(boeing)}
{plane(airbus), flies(airbus)}
{penguin(joe), not flies(joe)}

Learnt Theory:

The Set-Cover Loop

1. Select positive example.
2. Generate rule that covers the example.

$\{\texttt{bird(sparrow)}, \texttt{flies(sparrow)}\}$
$\{\texttt{bird(eagle)}, \texttt{flies(eagle)}\}$
$\{\texttt{plane(boeing)}, \texttt{flies(boeing)}\}$
$\{\texttt{plane(airbus)}, \texttt{flies(airbus)}\}$
$\{\texttt{penguin(joe)}, \texttt{not flies(joe)}\}$

Learnt Theory:
$\texttt{flies(boeing)} \leftarrow \texttt{plane(boeing)}.$

The Set-Cover Loop

1. Select positive example.
2. Generate rule that covers the example.
3. Generalize.

$\{\texttt{bird(sparrow)}, \texttt{flies(sparrow)}\}$
$\{\texttt{bird(eagle)}, \texttt{flies(eagle)}\}$
$\{\texttt{plane(boeing)}, \texttt{flies(boeing)}\}$
$\{\texttt{plane(airbus)}, \texttt{flies(airbus)}\}$
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Learnt Theory:
$\texttt{flies(X)} \leftarrow \texttt{plane(X)}.$

The Set-Cover Loop

1. Select positive example.
2. Generate rule that covers the example.
3. Generalize.
4. Remove covered positives.

{bird(sparrow), flies(sparrow)}
{bird(eagle), flies(eagle)}
{plane(boeing), flies(boeing)}
{plane(airbus), flies(airbus)}
{penguin(joe), not flies(joe)}

Learnt Theory:
flies(X) $\leftarrow$ plane(X).

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Learnt Theory:
$\texttt{flies(X)} \leftarrow \texttt{plane(X)}.$

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5. Repeat until no positives left (or other stopping criterion).

$\{\texttt{bird(sparrow)}, \texttt{flies(sparrow)}\}$
$\{\texttt{bird(eagle)}, \texttt{flies(eagle)}\}$

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Learnt Theory:
$\texttt{flies(X)} \leftarrow \texttt{plane(X)}.$
$\texttt{flies(sparrow)} \leftarrow \texttt{bird(sparrow)} \wedge \texttt{not penguin(sparrow)}.$

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2. Generate rule that covers the example.
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$\{\texttt{bird(sparrow)}, \texttt{flies(sparrow)}\}$
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$\{\texttt{penguin(joe)}, \texttt{not flies(joe)}\}$

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$\texttt{flies(X)} \leftarrow \texttt{plane(X)}.$
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The Set-Cover Loop

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2. Generate rule that covers the example.
3. Generalize.
4. Remove covered positives.
5. Repeat until no positives left (or other stopping criterion).

Stop!

Learnt Theory:
$\texttt{flies(X)} \leftarrow \texttt{plane(X)}.$
$\texttt{flies(X)} \leftarrow \texttt{bird(X)} \land \texttt{not penguin(X)}.$

Learning a Rule

- Heuristic search in a space ordered by generality.

Generality

- Generality relation
- A rule r_1 is more general that a rule r_2 if
  - $\{$examples covered by $r_2\} \subseteq \{$examples covered by $r_1\}$.
- Rule of thumb: "less constraint" rules are more general
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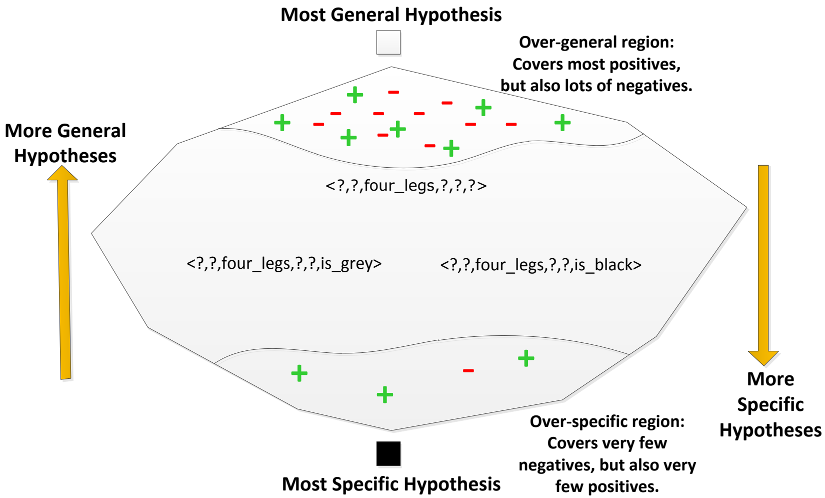
- A rule r_1 is more general that a rule r_2 if
  - $\{$examples covered by $r_2\} \subseteq \{$examples covered by $r_1\}$.
- Rule of thumb: "less constraint" rules are more general
  - Therefore they cover more examples.
- For example, which one is more general?

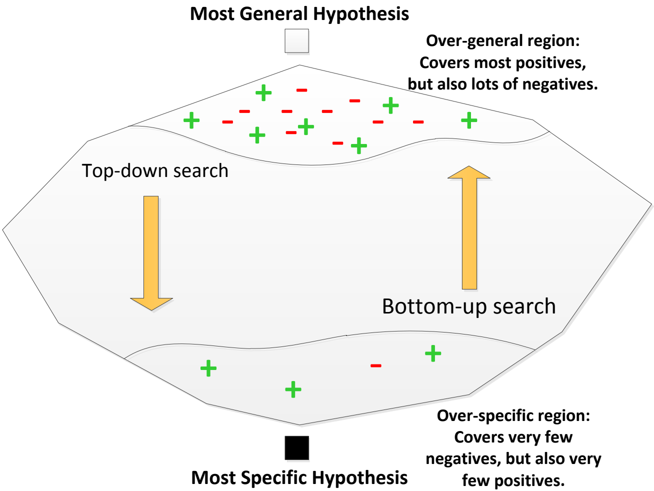
```
IF has_four_legs & has_whiskers THEN class = cat
IF has_four_legs & has_whiskers & is_grey THEN class = cat
```

Version Spaces

- Space ordered by generality.

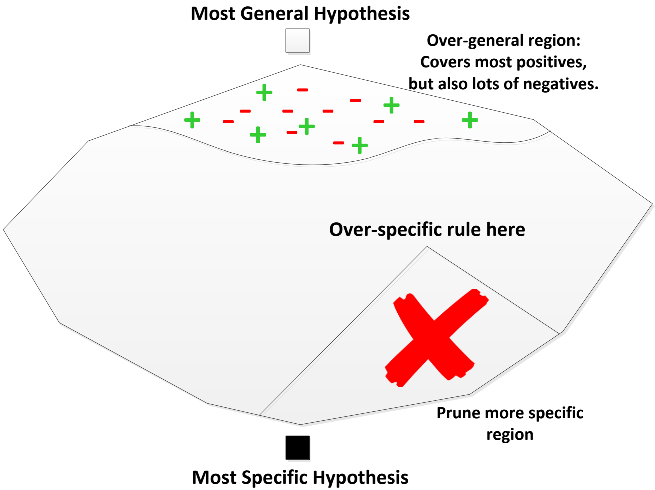


Version Spaces



- Top-down search: Start from over-general, gradually specialize to exclude negatives.
- Bottom-up search: Start from over-specific, gradually generalize to cover positives.

Version Spaces



- Pruning heuristics
- If a rule is already over-specific (covers too few positives), there is no need to look into its more specific region.

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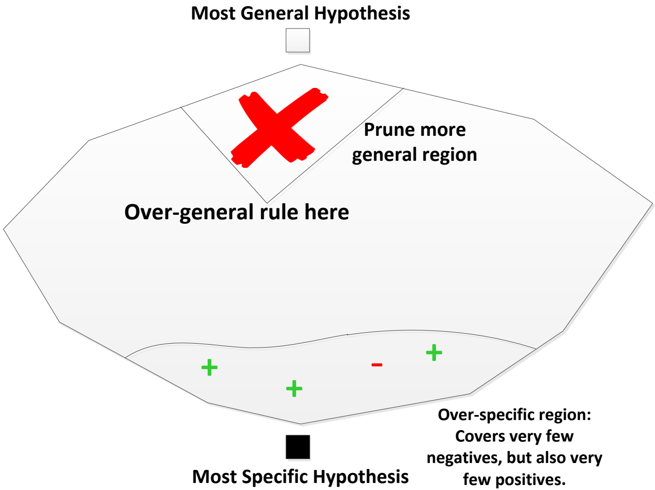

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- If a rule is over-general (covers too many negatives), there is no need to look into its more general region.

ILP Basics: Learning & Search

- The version space model has some nice properties.
- Can we "upgrade" it to First-Order Logic?
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- Problem: $r_1 \models_? r_2$ for arbitrary r_1, r_2 is undecidable (even for Horn logic).
- Use θ-subsumption as surrogate.

θ-subsumption

- Substitution $\theta = [X_1/t_1, \ldots, X_n/t_n]$: an assignment of terms t_i to variables X_i.
- A rule r_1 θ-subsumes a rule r_2 ($r_1 \preceq r_2$) iff
  $\exists\theta : [\mathit{head}(r_1)\theta = \mathit{head}(r_2)\ \&\ \mathit{body}(r_1)\theta \subseteq \mathit{body}(r_2)]$.

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$r_1 = \texttt{flies(X)} \leftarrow \texttt{bird(X)}$
$r_2 = \texttt{flies(Y)} \leftarrow \texttt{bird(Y)} \wedge \texttt{not penguin(Y)}$
$r_3 = \texttt{flies(tweety)} \leftarrow \texttt{bird(tweety)} \wedge \texttt{not penguin(tweety)}$
Then:
$r_1 \preceq r_2$ with $\theta = [X/Y]$.
$r_1 \preceq r_3$ with $\theta = [X/tweety]$.

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Then:
$r_1 \preceq r_2$ with $\theta = [X/Y]$.
$r_1 \preceq r_3$ with $\theta = [X/\mathit{tweety}]$.

- A theory H_1 θ-subsumes a theory H_2 iff
  $\forall r_1 \in H_1, \exists r_2 \in H_2 : r_1 \preceq r_2$.

θ-subsumption

Properties of θ-subsumption:

- If $r_1 \preceq r_2$ then $r_1 \models r_2$.
  - *the inverse does not hold*.
- If $r_1 \preceq r_2$ then $covers(r_2) \subseteq covers(r_1)$.
- θ-subsumption is decidable (but still, NP-complete).

θ-subsumption

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- If $r_1 \preceq r_2$ then $r_1 \vDash r_2$.
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- θ-subsumption is decidable (but still, NP-complete).

Therefore:

- θ-subsumption can be used as a surrogate for logical entailment.
- Version space (propositional) $\leftrightarrow$ subsumption lattice (relational).
- We essentially have the same search and pruning heuristics.

Learning a Rule

- Construct a search space (subsumption lattice).
  - Upper-bound: Most-general rule (rule with an empty body)
  - Lower-bound: Most-specific rule that covers a single example.
- Use search and pruning heuristics, along with a quality criterion (e.g. precision, recall, compression, info gain...) to find a "good" rule.

Learning a Rule: The subsumption Lattice

Top Clause ⊤: initiatedAt(*meet*(X, Y), T) $\leftarrow$

initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*active*(X), T).

initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*inactive*(Y), T).

...

initiatedAt(*meet*(X, Y), T) $\leftarrow$
holdsAt(*orientation*(X, Y, *45*), T).

Rest of clauses generated by adding one condition from ⊥ to the body of ⊤

initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*active*(X), T),
happensAt(*inactive*(Y), T).

initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*active*(X), T),
holdsAt(*close*(X, Y, *25*), T).

... ...

initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*active*(X), T),
happensAt(*inactive*(Y), T),
holdsAt(*close*(X, Y, *25*), T).

... ...

... ...

Bottom Clause ⊥ :
initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*active*(X), T), happensAt(*inactive*(Y), T), holdsAt(*close*(X, Y, *25*), T),
holdsAt(*close*(Y, X, *25*), T), *not* happensAt(*inactive*(X), T), *not* happensAt(*abrupt*(X), T),
not happensAt(*running*(X), T), happensAt(*inactive*(Y), T), *not* happensAt(*active*(Y), T),
not happensAt(*running*(Y), T), *not* happensAt(*abrupt*(Y), T), holdsAt(*orientation*(X, Y, *45*), T).

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... ...

initiatedAt(*meet*(X, Y), T) ←
happensAt(*active*(X), T),
happensAt(*inactive*(Y), T),
holdsAt(*close*(X, Y, *25*), T).

...

... ...

Ordered by θ-subsumption $\preceq$:
If $r_1 \preceq r_2$ then covers$(r_2, e) \Rightarrow$ covers(r_1, e)
for all examples e

...

Bottom Clause ⊥ :
initiatedAt(*meet*(X, Y), T) ←
happensAt(*active*(X), T), happensAt(*inactive*(Y), T), holdsAt(*close*(X, Y, *25*), T),
holdsAt(*close*(Y, X, *25*), T), *not* happensAt(*inactive*(X), T), *not* happensAt(*abrupt*(X), T),
not happensAt(*running*(X), T), happensAt(*inactive*(Y), T), *not* happensAt(*active*(Y), T),
not happensAt(*running*(Y), T), *not* happensAt(*abrupt*(Y), T), holdsAt(*orientation*(X, Y, *45*), T).

Learning a Rule: Search

Positives not covered

Top Clause ⊤: initiatedAt(*meet*(*X*, *Y*), *T*) ←

initiatedAt(*meet*(*X*, *Y*), *T*) ← happensAt(*active*(*X*), *T*).

initiatedAt(*meet*(*X*, *Y*), *T*) ← happensAt(*inactive*(*Y*), *T*).

...

...

initiatedAt(*meet*(*X*, *Y*), *T*) ← happensAt(*active*(*X*), *T*), happensAt(*inactive*(*Y*), *T*).

initiatedAt(*meet*(*X*, *Y*), *T*) ← happensAt(*active*(*X*), *T*), holdsAt(*close*(*X*, *Y*, *25*), *T*).

initiatedAt(*meet*(*X*, *Y*), *T*) ←
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...

...

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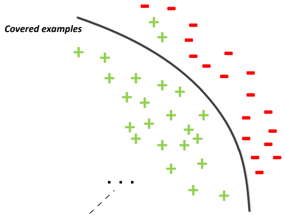

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Learning a Rule: Search

Generalization ↑

Top Clause ⊤: initiatedAt(*meet*(X, Y), T) ←

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. . .

. . .

initiatedAt(*meet*(X, Y), T) ←
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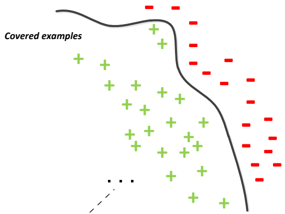
. . .

. . .

. . .

. . .



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Learning a Rule: Search

Negatives covered

Top Clause ⊤: initiatedAt(*meet*(X, Y), T) ←

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. . .

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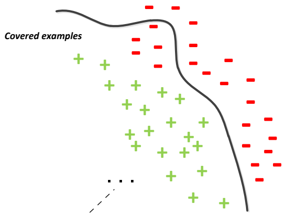

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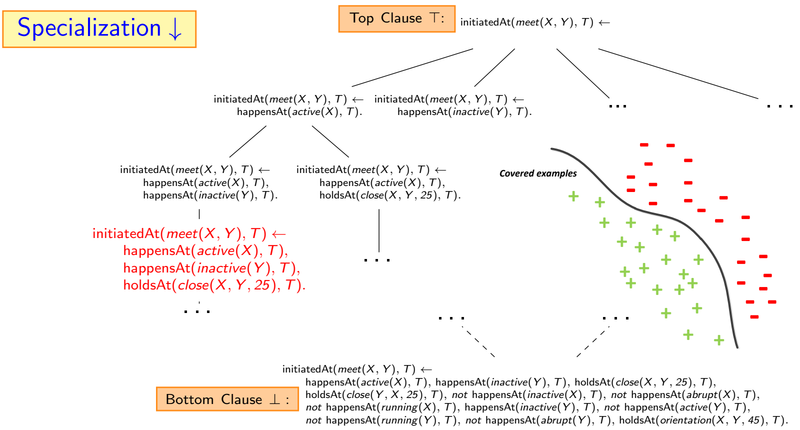
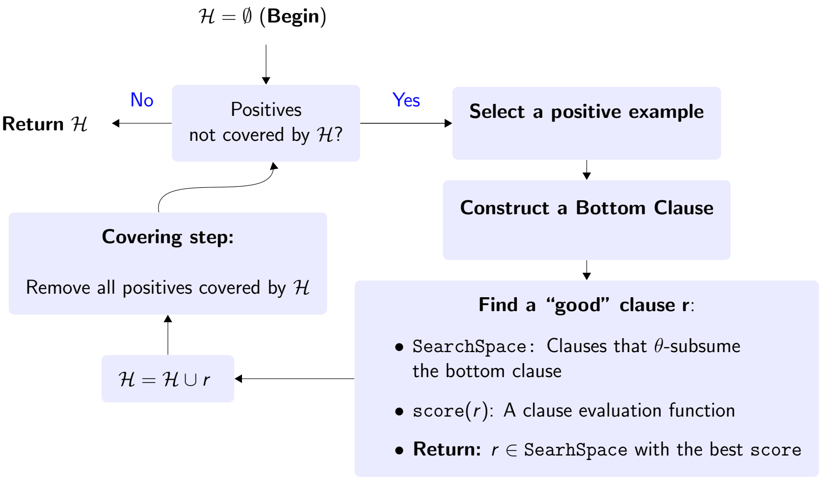
Learning a Rule: Search



Putting it All Together



ILP Basics: Summary

- We are given training examples representing true/false "snapshots" of the target concept.
- Some BK encoding things we know about the domain.
- Some hypothesis language.
- We use a "covers" relation based on logical entailment.
- and θ-subsumption as a notion of generality.
- Based on generality we build search spaces.
- Using a rule quality criterion, in addition to search and pruning heuristics we look for "good" rules within the search spaces.
- We learn one rule at a time until some stopping criterion is met.
  - For example, until we cover all positives, until we reach a maximum theory size etc.

Overview

- Part I: Dealing with Interacting Entities in Dynamic Domains.
  - Norm-governed systems.
  - Complex Event Recognition systems.
  - Logical specifications of domain dynamics.
  - The Event Calculus.
- Part II: Learning logical specifications of domain dynamics.
  - Basics of Logical & Relational Learning.
  - Learning with the Event Calculus.
  - Abductive-Inductive learning.
  - Learning from relational data streams.
- Part IV: Statistical Relational Learning.
  - Markov Logic Networks.
  - Online structure & weight learning.

Learning with the Event Calculus

- The classical ILP strategy works for
  - Learning a single concept.
  - Learning multiple **independent** concepts.
- This is not the case with the Event Calculus.
  - We want to learn theories of temporal specifications.
  - In the form of initiation & termination rules.
  - Which are **not** independent from each other.

Learning with the Event Calculus

- Inferences are non-monotonic:
  - Given: $\texttt{initiatedAt}(\texttt{event}_1, 10)$.
  - ? $\texttt{holdsAt}(\texttt{event}_1, 20)$.
    - yes.

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  - As a result, we need to retract our previous answer.
- As a result of non-monotonicity
  - Iterative (covering) rule learning techniques do not work.
  - They are based on the monotonicity assumption that adding new rules to a theory increases the example coverage of the theory.
  - Which is not the case, E.g. adding a termination rules reduces the example coverage of the theory.

Learning with the Event Calculus

Event Calculus as a Reasoning Engine

$\mathsf{holdsAt}(F,\, T+1) \leftarrow$
$\quad \mathsf{initiatedAt}F,\, T)$

$\mathsf{holdsAtAt}(F,\, T+1) \leftarrow$
$\quad \mathsf{holdsAt}(F,\, T),$
$\quad \mathit{not}\ \mathsf{terminatedAt}(F,\, T).$

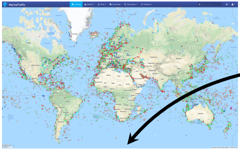
Very efficient inference: *Artikis et al. An Event Calculus for Event Recognition, TKDE, 2015.*

Input ▶ Recognition ▶ Output ■

· · · Simple Events · · ·

Event Recognition System

· · · Complex Events · · ·



AIS signals,

contextual info (ports, weather, environment...)

Complex Event Definitions

$\mathsf{holdsAt}(\mathit{rendezVous}(\mathit{vessel}_1, \mathit{vessel}_2), 10)$
$\mathsf{holdsAt}(\mathit{rendezVous}(\mathit{vessel}_1, \mathit{vessel}_2), 11)$
$\mathsf{holdsAt}(\mathit{rendezVous}(\mathit{vessel}_1, \mathit{vessel}_2), 12)$
. . .

Learning this

$\mathsf{initiatedAt}(\mathit{rendezVous}(X, Y), T) \leftarrow$
$\quad \mathsf{happensAt}(\mathit{stopped}(X), T),$
$\quad \mathsf{happensAt}(\mathit{lowSpeed}(Y), T),$
$\quad \mathit{farFromPorts}(X, T),$
$\quad \mathit{farFromPorts}(Y, T),$
$\quad \mathit{closeProximity}(X, Y, T).$

$\mathsf{terminatedAt}(\mathit{rendezVous}(X, Y), T) \leftarrow$
$\quad \mathsf{happensAt}(\mathit{travelSpeed}(X), T),$
$\quad \mathit{not}\ \mathit{closeProximity}(X, Y, T).$

From These

Learning with the Event Calculus

Event Calculus as a Reasoning Engine

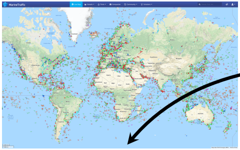
holdsAt(F, $T+1$) ←
  initiatedAtF, T)

holdsAtAt(F, $T+1$) ←
  holdsAt(F, T),
  not terminatedAt(F, T).

Very efficient inference: *Artikis et al. An Event Calculus for Event Recognition, TKDE, 2015.*

Input ▶ Recognition ▶ Output ■

Simple Events → Event Recognition System → Complex Events



AIS signals,
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Complex Event Definitions

holdsAt($rendezVous(vessel_1, vessel_2), 10$)
holdsAt($rendezVous(vessel_1, vessel_2), 11$)
holdsAt($rendezVous(vessel_1, vessel_2), 12$)
...

Learn this

initiatedAt($rendezVous(X, Y), T$) ←
  happensAt($stopped(X), T$),
  happensAt($lowSpeed(Y), T$),
  $farFromPorts(X, T)$,
  $farFromPorts(Y, T)$,
  $closeProximity(X, Y, T)$.

terminatedAt($rendezVous(X, Y), T$) ←
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From These

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Event Calculus as a Reasoning Engine

holdsAt(F, $T+1$) $\leftarrow$
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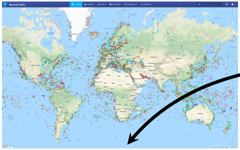
Input ▶ Recognition ▶ Output ■

Simple Events

Event Recognition System

Complex Events



AIS signals,

contextual info (ports, weather, environment...)

Complex Event

Ground Truth predicates differ from target predicates!

holdsAt($rendezVous(vessel_1, vessel_2), 10$)
holdsAt($rendezVous(vessel_1, vessel_2), 11$)
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...

Learn this

initiatedAt($rendezVous(X, Y)$, T) $\leftarrow$
  happensAt($stopped(X)$, T),
  happensAt($lowSpeed(Y)$, T),
  $farFromPorts(X, T)$,
  $farFromPorts(Y, T)$,
  $closeProximity(X, Y, T)$.

terminatedAt($rendezVous(X, Y)$, T) $\leftarrow$
  happensAt($travelSpeed(X)$, T),
  $not\ closeProximity(X, Y, T)$.

From These

Abductive Logic Programming (ALP)

- Abduction:
  - Hypothetical reasoning to the best explanation under incomplete information.
- ALP
  - Given:
    - A logic program H.
    - A set of observations O (logical facts).
    - A set of integrity constraints IC.
    - A set of predicate symbols A.
  - Find:
    - A set of *abductive explanations* $\Delta \subseteq A$ s.t. $H \cup \Delta \models O$ and $H \cup \Delta \cup IC$ is consistent.
  - Formal correspondence between NAF semantics and ALP.

ALP: A Simple Example

Observations:
$\texttt{holdsAt}(\texttt{meeting}(\texttt{id}_1, \texttt{id}_2), 10).$
$\texttt{holdsAt}(\texttt{meeting}(\texttt{id}_1, \texttt{id}_2), 11).$
$\texttt{not holdsAt}(\texttt{meeting}(\texttt{id}_1, \texttt{id}_2), 12).$
$\texttt{time}(1..20).$

H : The axioms of inertia (Event Calculus).

$A = \{\texttt{initiatedAt}/2, \texttt{terminatedAt}/2\}.$

$IC = \texttt{false} \leftarrow \texttt{initiatedAt}(\texttt{F}, \texttt{T}) \wedge \texttt{terminatedAt}(\texttt{F}, \texttt{T}).$

ALP: A Simple Example

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$\texttt{holdsAt}(\texttt{meeting}(\texttt{id}_1, \texttt{id}_2), 10).$
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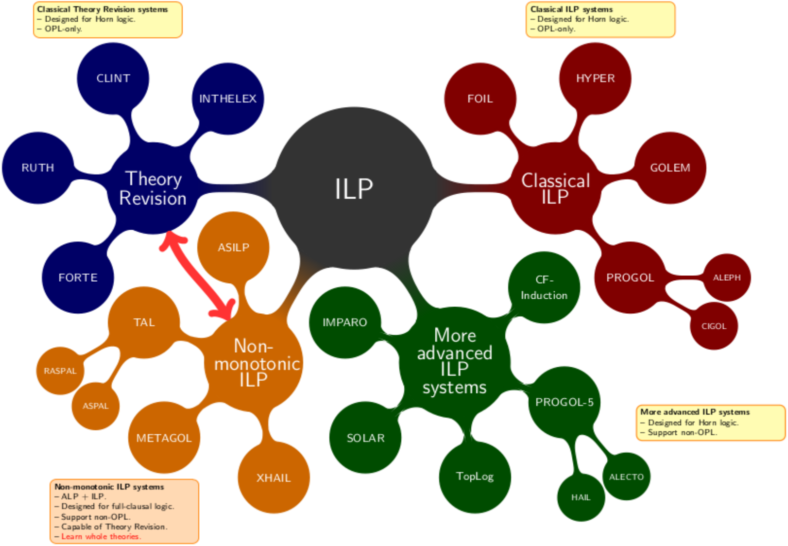
$A = \{\texttt{initiatedAt}/2, \texttt{terminatedAt}/2\}.$

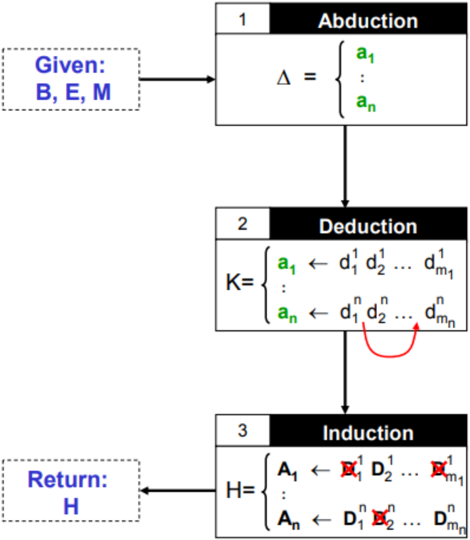
$IC = \texttt{false} \leftarrow \texttt{initiatedAt}(\texttt{F}, \texttt{T}) \wedge \texttt{terminatedAt}(\texttt{F}, \texttt{T}).$

$\Delta = \{\texttt{initiatedAt}(\texttt{meeting}(\texttt{id}_1, \texttt{id}_2), 9), \texttt{terminatedAt}(\texttt{meeting}(\texttt{id}_1, \texttt{id}_2), 11)\}.$

Non-monotonic Learning



Non-monotonic Learning (The XHAIL Algorithm)



Find a set of (head) atoms that abductively explain the positive and negative examples:

i.e. $B \wedge a_1 \wedge \ldots \wedge a_n \models E$

Find a set of (body) literals that deductively follow from the prior knowledge:

i.e. $B \models d_1^1 \wedge \ldots \wedge d_{m_n}^n$

Find a compressive theory that theta-subsumes the Kernel Set and explains the examples

i.e. $H \geq K$ and $B \wedge H \models E$

Slide from Ray O., *Using Abduction for Induction of Normal Logic Programs*, AIAI-2006.

The XHAIL Algorithm (Example)

Examples:

$\texttt{happensAt}(\texttt{walking}(\texttt{id}_1), 9)$
$\texttt{coords}(\texttt{id}_1, 201, 454, 9)$
$\texttt{holdsAt}(\texttt{moving}(\texttt{id}_1, \texttt{id}_2), 10)$
$\ldots$
$\texttt{happensAt}(\texttt{running}(\texttt{id}_5), 20)$
$\texttt{direction}(\texttt{id}_3, 270, 20)$
$\texttt{not holdsAt}(\texttt{moving}(\texttt{id}_3, \texttt{id}_5), 21)$
$\ldots$

Abduction:

$\texttt{initiatedAt}(\texttt{moving}(\texttt{id}_1, \texttt{id}_2), 9)$
$\texttt{terminatedAt}(\texttt{moving}(\texttt{id}_3, \texttt{id}_5), 20)$

The XHAIL Algorithm (Example)

Examples:

$\texttt{happensAt}(\texttt{walking}(\texttt{id}_1), 9)$
$\texttt{coords}(\texttt{id}_1, 201, 454, 9)$
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...

Abduction:

$\texttt{initiatedAt}(\texttt{moving}(\texttt{id}_1, \texttt{id}_2), 9)$
$\texttt{terminatedAt}(\texttt{moving}(\texttt{id}_3, \texttt{id}_5), 20)$

Bottom Theory/Kernel Set:

$\texttt{initiatedAt}(\texttt{moving}(\texttt{id}_1, \texttt{id}_2), 9) \leftarrow$
$\quad \texttt{happensAt}(\texttt{walking}(\texttt{id}_1), 9),$
$\quad \texttt{happensAt}(\texttt{walking}(\texttt{id}_2), 9),$
$\quad \texttt{not happensAt}(\texttt{running}(\texttt{id}_1), 9),$
$\quad \texttt{not happensAt}(\texttt{active}(\texttt{id}_2), 9),$
$\quad \texttt{holdsAt}(\texttt{close}(\texttt{id}_1, \texttt{id}_2, 35), 9),$
$\quad \texttt{holdsAt}(\texttt{orientation}(\texttt{id}_1, \texttt{id}_2, 45), 9).$

$\texttt{terminatedAt}(\texttt{moving}(\texttt{id}_3, \texttt{id}_5), 20) \leftarrow$
$\quad \texttt{happensAt}(\texttt{walking}(\texttt{id}_3), 20),$
$\quad \texttt{happensAt}(\texttt{running}(\texttt{id}_5), 20),$
$\quad \texttt{not happensAt}(\texttt{abrupt}(\texttt{id}_1), 9),$
$\quad \texttt{not happensAt}(\texttt{active}(\texttt{id}_2), 9),$
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The XHAIL Algorithm (Example)

Examples:

happensAt(walking(id_1), 9)
coords(id_1, 201, 454, 9)
holdsAt(moving(id_1, id_2), 10)
...
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direction(id_3, 270, 20)
not holdsAt(moving(id_3, id_5), 21)
...

Abduction:

initiatedAt(moving(id_1, id_2), 9)
terminatedAt(moving(id_3, id_5), 20)

Bottom Theory/Kernel Set:

initiatedAt(moving(X, Y), T) ←
  happensAt(walking(X), T),
  happensAt(walking(Y), T),
  holdsAt(close(X, Y, 35), T),
  not happensAt(running(X), T),
  not happensAt(active(Y), T),
  holdsAt(orientation(X, Y, 45), T).

terminatedAt(moving(X, Y), T) ←
  happensAt(walking(X), T),
  happensAt(running(Y), T),
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  not happensAt(active(Y), T),
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The XHAIL Algorithm (Example)

Examples:

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Hypothesis:

initiatedAt(moving(X, Y), T) ←
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terminatedAt(moving(X, Y), T) ←
happensAt(running(Y), T),
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Induction as Abductive Search

Bottom Theory/Kernel Set:

$\mathtt{initiatedAt(moving(X,Y),T)} \leftarrow$
$\quad \mathtt{happensAt(walking(X),T)},$
$\quad \mathtt{happensAt(walking(Y),T)},$
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$\quad \cancel{\text{not happensAt(running(X),T)}},$
$\quad \cancel{\text{not happensAt(active(Y),T)}},$
$\quad \mathtt{holdsAt(orientation(X,Y,45),T)}.$

$\mathtt{terminatedAt(moving(X,Y),T)} \leftarrow$
$\quad \cancel{\text{happensAt(walking(X),T)}},$
$\quad \mathtt{happensAt(running(Y),T)},$
$\quad \cancel{\text{not happensAt(abrupt(X),T)}},$
$\quad \cancel{\text{not happensAt(active(Y),T)}},$
$\quad \mathtt{not\ holdsAt(close(X,Y,35),T)},$
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$\longrightarrow$

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holdsAt(close(X, Y, 35), T),
X, Y, 45), T),

), T) ←
T),
, 35), T).

Replace the i-th rule $\alpha^i \leftarrow \delta_1^i, \ldots, \delta_n^i$ in the Kernel Set with the following program:

$\alpha^{\mathtt{i}} \leftarrow \mathtt{use(i, 0), try(i, 1,}\ \delta_{\mathtt{1}}^{\mathtt{i}}\mathtt{)}.$
$\mathtt{try(i, 1,}\ \delta_{\mathtt{1}}^{\mathtt{i}}\mathtt{)} \leftarrow \mathtt{not\ use(i, 1)}.$
$\mathtt{try(i, 1,}\ \delta_{\mathtt{1}}^{\mathtt{i}}\mathtt{)} \leftarrow \mathtt{use(i, 1),}\ \delta_{\mathtt{1}}^{\mathtt{i}}.$
...
$\alpha^i \leftarrow use(i, 0), try(i, n, \delta_n^i).$
$\mathtt{try(i, n,}\ \delta_{\mathtt{n}}^{\mathtt{i}}\mathtt{)} \leftarrow \mathtt{not\ use(i, n)}.$
$\mathtt{try(i, n,}\ \delta_{\mathtt{1}}^{\mathtt{i}}\mathtt{)} \leftarrow \mathtt{use(i, n),}\ \delta_{\mathtt{n}}^{\mathtt{i}}.$

Specify goal & solve (directly, with an Answer Set Solver!):

truePos(E) ← holdsAt(E, T), positiveExmpl(E).
falsePos(E) ← holdsAt(E, T), not positiveExmpl(E).
{use(I, J)} ← ruleId(I), literalId(J). *(Abduction via choice rule.)*
maximize{truePos/1}.
minimize{falsePos/1, use/2}.

H is obtained from the Kernel Set by removing every body atom $\delta_{\mathtt{i}}^{\mathtt{j}}$ for which the abducible use(i, j) is not in Δ, and removing every rule whose head atom $\mathtt{a_i}$ does not have a corresponding atom use(0, i) in Δ.

Theory Revision

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  - Formal semantics.
  - Capable of learning multi-concept theories, recursive concepts etc.
  - Does not scale.

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- The basic ideas behind XHAIL can be used for **Theory Revision (TR).**
  - Possible remedy for scalability issues.
- Data are presented in batches/chunks.
- A theory is constructed from the first batch.
- As new batches arrive the theory is continuously revised to account for the new observations.
  - Add new rules.
  - Remove existing (redundant) rules.
  - Specialize rules.
  - The TR process is guided by optimizing (locally, current batch only) example coverage + theory complexity.

Theory Revision

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  - Specialize rules.
  - The TR process is guided by optimizing (locally, current batch only) example coverage + theory complexity.
- How large should the batches be?
  - Larger batches mean more "globally-good" revisions, but also, harder to process.

Overview

- Part I: Dealing with Interacting Entities in Dynamic Domains.
  - Norm-governed systems.
  - Complex Event Recognition systems.
  - Logical specifications of domain dynamics.
  - The Event Calculus.
- Part II: Learning logical specifications of domain dynamics.
  - Basics of Logical & Relational Learning.
  - Learning with the Event Calculus.
  - Abductive-Inductive learning.
- Part III: Scalable learning.
  - Non-monotonic Theory Revision.
  - Learning from relational data streams.
- Part IV: Statistical Relational Learning.
  - Markov Logic Networks.
  - Online structure & weight learning.

Online Inductive Logic Programming

Challenge:

- Inductive Logic Programming algorithms are batch learners.
  - Each candidate in the search space is evaluated on the entire dataset.

Goal:

- Online learning:
  - Examples arrive in a stream.
  - Each example is “seen” once.

Approach:

- Make decisions from subsets of the stream:
  - Decisions are optimal “locally”.
  - Decisions are optimal “globally”...
    - within an error margin ϵ,
    - with probability $1-\delta$.

The Hoeffding Bound

- X is a random variable.
- $X_1, \ldots, X_N$ are N independent observations of X's values.
- Let $\bar{X}$ be the known, observed mean of X.
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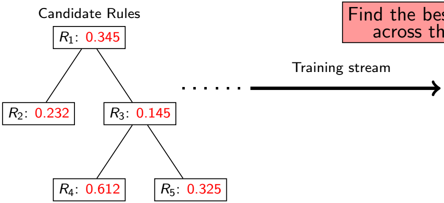
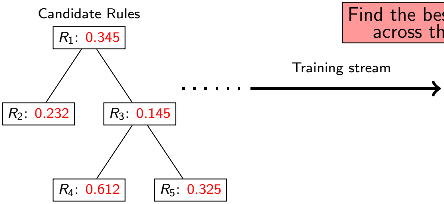
- Let $\bar{X}$ be the known, observed mean of X.
- Let $\hat{X}$ be the unknown, true mean of X.
- Then:
  $\bar{X} - \epsilon \leq \hat{X} \leq \bar{X} + \epsilon$, with probability $1 - \delta$, where $\epsilon = \sqrt{\frac{ln(1/\delta)}{2N}}$

Online Rule Learning



Find the best candidate across the stream

Online Rule Learning

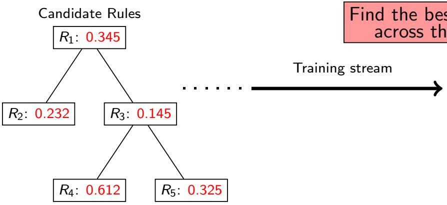


Find the best candidate across the stream

As examples stream in...

Monitor $\bar{X} = \overline{score}_{BestRule} - \overline{score}_{SecondBestRule}$

Online Rule Learning



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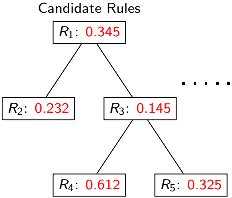
Monitor $\bar{X} = \overline{score}_{BestRule} - \overline{score}_{SecondBestRule}$

Continue until the number N of examples

makes $\bar{X} > \epsilon = \sqrt{\frac{ln(1/\delta)}{2N}}$

Online Rule Learning



Find the best candidate across the stream

Training stream

$\bar{X} - \epsilon \leq \hat{X} \leq \bar{X} + \epsilon$, where $\epsilon = \sqrt{\frac{ln(1/\delta)}{2N}}$

As examples stream in...

Monitor $\bar{X} = \overline{score}_{BestRule} - \overline{score}_{SecondBestRule}$

Continue until the number N of examples

makes $\bar{X} > \epsilon = \sqrt{\frac{ln(1/\delta)}{2N}}$

Then

$\bar{X} - \epsilon > 0 \Rightarrow$

$\hat{X} > 0 \Rightarrow$

BestRule is indeed the best rule,

with probability $1-\delta$.

Online Hill-Climbing

Top Clause $\top$: initiatedAt(*meet*(X, Y), T) $\leftarrow$

initiatedAt(*meet*(X, Y), T) $\leftarrow$ happensAt(*active*(X), T).

initiatedAt(*meet*(X, Y), T) $\leftarrow$ happensAt(*inactive*(Y), T).

...

initiatedAt(*meet*(X, Y), T) $\leftarrow$ holdsAt(*orientation*(X, Y, *45*), T).

Training stream

... ...

Bottom Clause $\bot$: initiatedAt(*meet*(X, Y), T) $\leftarrow$
happensAt(*active*(X), T), happensAt(*inactive*(Y), T), holdsAt(*close*(X, Y, *25*), T),
holdsAt(*close*(Y, X, *25*), T), *not* happensAt(*inactive*(X), T), *not* happensAt(*abrupt*(X), T),
not happensAt(*running*(X), T), happensAt(*inactive*(Y), T), *not* happensAt(*active*(Y), T),
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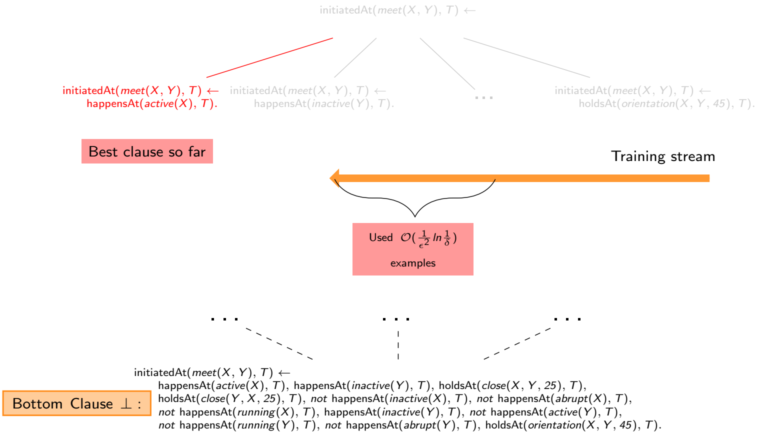
Online Hill-Climbing



Online Hill-Climbing

initiatedAt(*meet*(*X*, *Y*), *T*) ←

initiatedAt(*meet*(*X*, *Y*), *T*) ←
happensAt(*active*(*X*), *T*).

initiatedAt(*meet*(*X*, *Y*), *T*) ←
happensAt(*inactive*(*Y*), *T*).

...

initiatedAt(*meet*(*X*, *Y*), *T*) ←
holdsAt(*orientation*(*X*, *Y*, *45*), *T*).

initiatedAt(*meet*(*X*, *Y*), *T*) ←
happensAt(*active*(*X*), *T*),
happensAt(*inactive*(*Y*), *T*).

initiatedAt(*meet*(*X*, *Y*), *T*) ←
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Training stream

Used $\mathcal{O}(\frac{1}{\epsilon^2} ln \frac{1}{\delta})$

examples

... ...

Bottom Clause ⊥ :

initiatedAt(*meet*(*X*, *Y*), *T*) ←
happensAt(*active*(*X*), *T*), happensAt(*inactive*(*Y*), *T*), holdsAt(*close*(*X*, *Y*, *25*), *T*),
holdsAt(*close*(*Y*, *X*, *25*), *T*), *not* happensAt(*inactive*(*X*), *T*), *not* happensAt(*abrupt*(*X*), *T*),
not happensAt(*running*(*X*), *T*), happensAt(*inactive*(*Y*), *T*), *not* happensAt(*active*(*Y*), *T*),
not happensAt(*running*(*Y*), *T*), *not* happensAt(*abrupt*(*Y*), *T*), holdsAt(*orientation*(*X*, *Y*, *45*), *T*).

Online Hill-Climbing

initiatedAt(*meet*(X, Y), T) ←

initiatedAt(*meet*(X, Y), T) ← happensAt(*active*(X), T).

initiatedAt(*meet*(X, Y), T) ← happensAt(*inactive*(Y), T).

...

initiatedAt(*meet*(X, Y), T) ← holdsAt(*orientation*(X, Y, *45*), T).

initiatedAt(*meet*(X, Y), T) ← happensAt(*active*(X), T), happensAt(*inactive*(Y), T).

initiatedAt(*meet*(X, Y), T) ← happensAt(*active*(X), T), holdsAt(*close*(X, Y, *25*), T).

Best clause so far

Training stream

Used $\mathcal{O}(\frac{1}{\epsilon^2} \ln \frac{1}{\delta})$ examples

Used $\mathcal{O}(\frac{1}{\epsilon^2} \ln \frac{1}{\delta})$ examples

... ...

Bottom Clause $\perp$:

initiatedAt(*meet*(X, Y), T) ←
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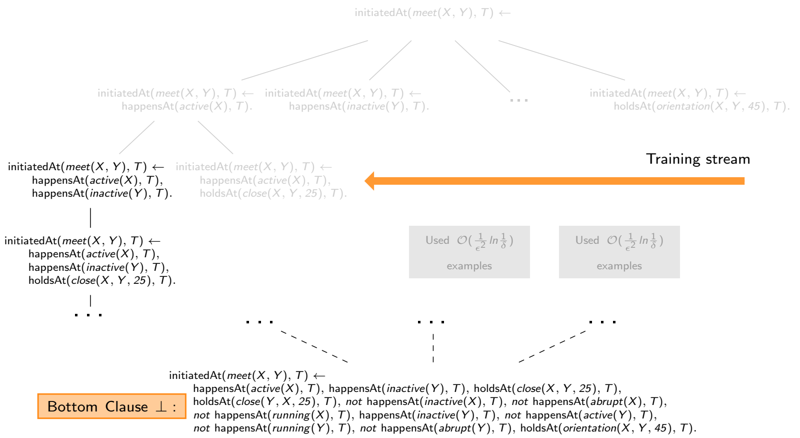

Features

Clause pruning:

- Often, “bad” clauses are constructed (e.g. from noisy examples).
- These are discarded when:
  - they do not “change” (get specialized) for sufficiently enough time
  - and their score is below a threshold.

Features

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- Any-time algorithm
- In practice an output clause must have been evaluated on N_{min} examples.

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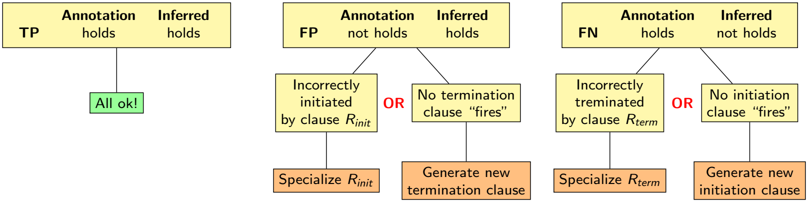
Warm-up period:

- Any-time algorithm
- In practice an output clause must have been evaluated on N_{min} examples.

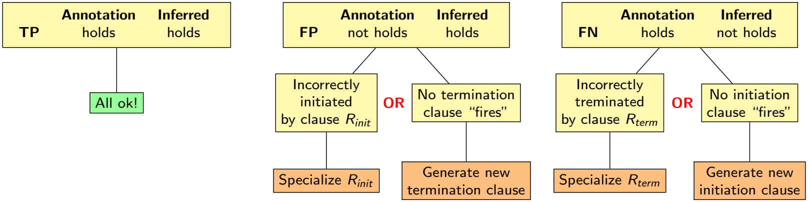
Tie breaking:

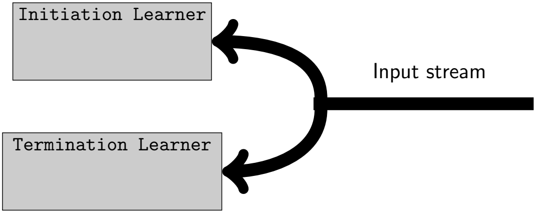
- When the best & the second-best clause have very similar scores...
- Break ties based on a pre-defined threshold, instead of waiting until the Hoeffding bound test succeeds.

Learning Sets of Clauses



Learning Sets of Clauses





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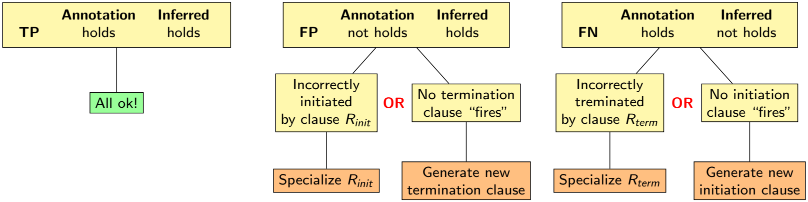

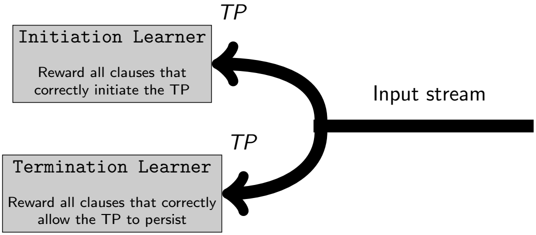

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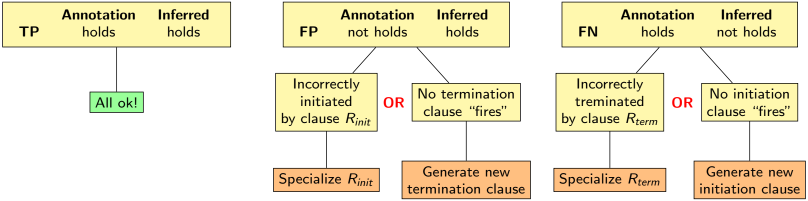

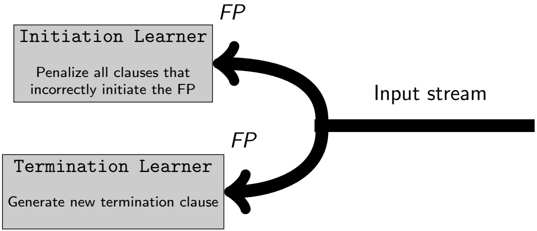

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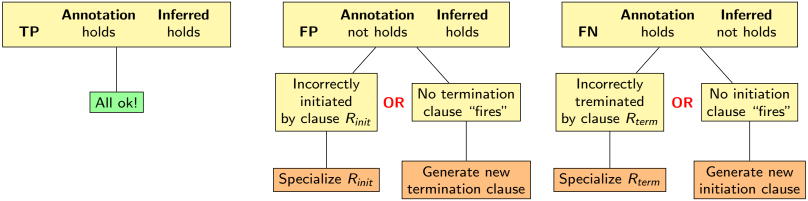
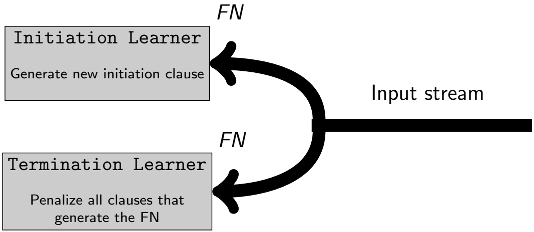
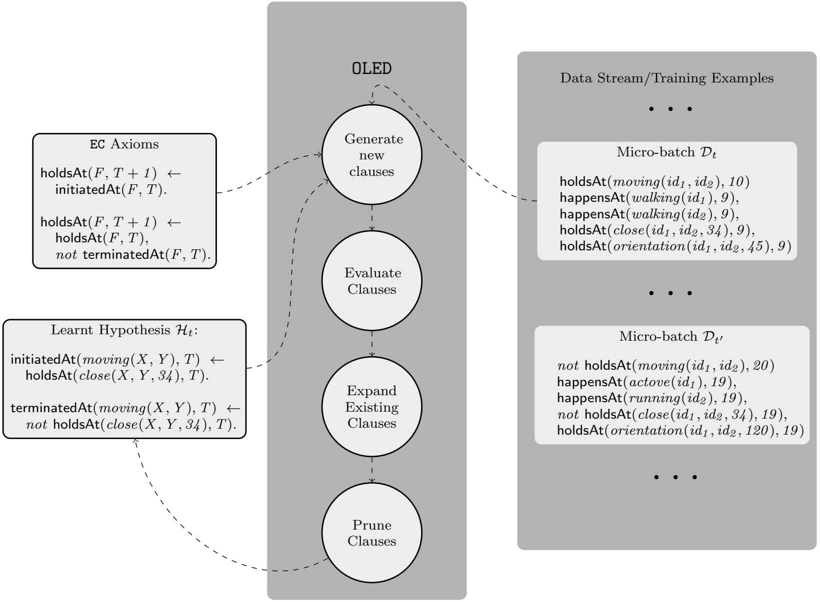




OLED


OLED
Generate new clauses
Evaluate Clauses
Expand Existing Clauses
Prune Clauses
EC Axioms
holdsAt$(F, T+1) \leftarrow$
initiatedAt(F, T).
holdsAt$(F, T+1) \leftarrow$
holdsAt(F, T),
not terminatedAt(F, T).
Learnt Hypothesis $\mathcal{H}_t$:
initiatedAt$(moving(X, Y), T) \leftarrow$
holdsAt$(close(X, Y, 34), T)$.
terminatedAt$(moving(X, Y), T) \leftarrow$
not holdsAt$(close(X, Y, 34), T)$.
Data Stream/Training Examples
Micro-batch $\mathcal{D}_t$
holdsAt$(moving(id_1, id_2), 10)$
happensAt$(walking(id_1), 9)$,
happensAt$(walking(id_2), 9)$,
holdsAt$(close(id_1, id_2, 34), 9)$,
holdsAt$(orientation(id_1, id_2, 45), 9)$
Micro-batch $\mathcal{D}_{t'}$
not holdsAt$(moving(id_1, id_2), 20)$
happensAt$(actove(id_1), 19)$,
happensAt$(running(id_2), 19)$,
not holdsAt$(close(id_1, id_2, 34), 19)$,
holdsAt$(orientation(id_1, id_2, 120), 19)$

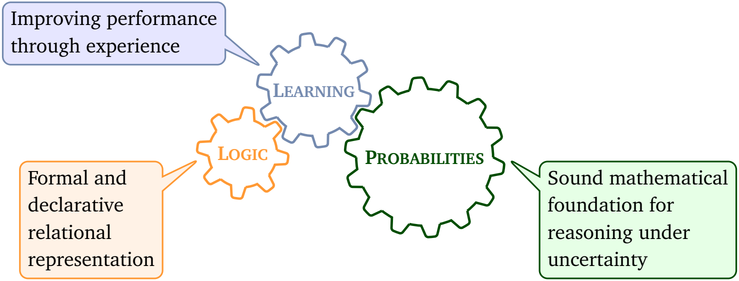
Comparison

	Method	F_1-score	Theory size	Time (sec)
Moving	EC_{crisp}	0.751	28	–
	EC_{MM}	**0.890**	28	1692
	XHAIL	0.841	**14**	7836
	OLED	0.812	34	**12**
Meeting	EC_{crisp}	0.762	23	–
	EC_{MM}	**0.863**	23	1133
	XHAIL	0.861	**15**	7248
	OLED	0.836	29	**23**

Overview

- Part I: Dealing with Interacting Entities in Dynamic Domains.
  - Norm-governed systems.
  - Complex Event Recognition systems.
  - Logical specifications of domain dynamics.
  - The Event Calculus.
- Part II: Learning logical specifications of domain dynamics.
  - Basics of Logical & Relational Learning.
  - Learning with the Event Calculus.
  - Abductive-Inductive learning.
- Part III: Scalable learning.
  - Non-monotonic Theory Revision.
  - Learning from relational data streams.
- Part IV: Statistical Relational Learning.
  - Markov Logic Networks.
  - Online structure & weight learning.

Statistical Relational Learning



ProbLog

- A probabilistic logic programming language.
- Allows for independent probabilistic facts prob::fact.
  - prob indicates the probability that fact is part of a possible world.
  - Facts are random variables.

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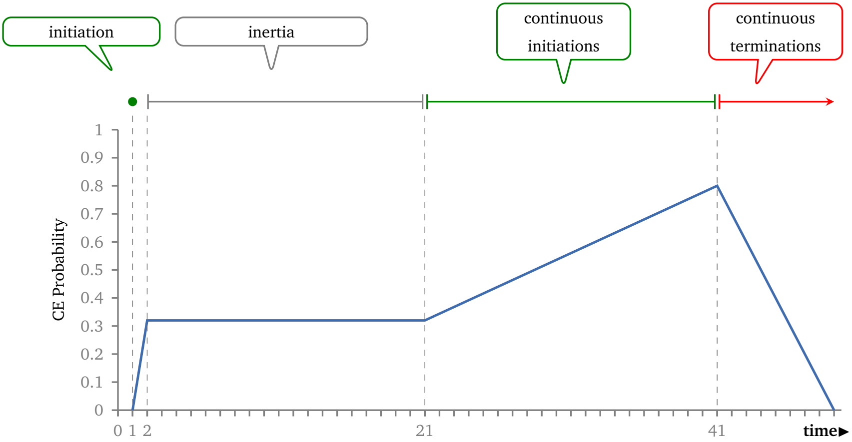
- Rules are written as in classic Prolog.
- The probability of a query q imposed on a ProbLog database *(success probability)* is computed by the following formula:

$$P_s(q) = P\left(\bigvee_{e \in Proofs(q)} \; \bigwedge_{f_i \in e} f_i \right)$$

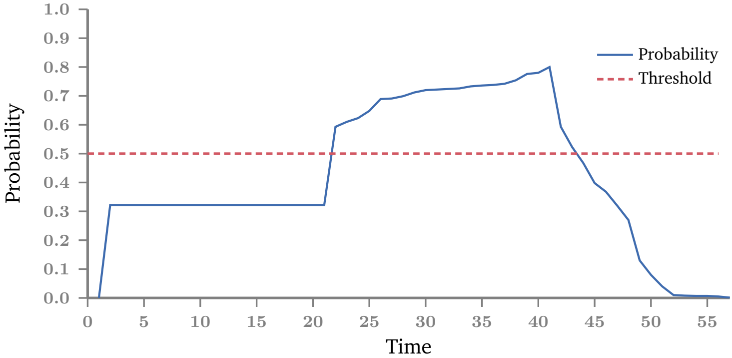
Event Recognition using ProbLog

Input	Output
340 0.45 :: $inactive(id_0)$	340 0.41 :: $left\_object(id_1, id_0)$
340 0.80 :: $p(id_0) = (20.88, -11.90)$	340 0.55 :: $moving(id_2, id_3)$
340 0.55 :: $appear(id_0)$	
340 0.15 :: $walking(id_2)$	
340 0.80 :: $p(id_2) = (25.88, -19.80)$	
340 0.25 :: $active(id_1)$	
340 0.66 :: $p(id_1) = (20.88, -11.90)$	
340 0.70 :: $walking(id_3)$	
340 0.46 :: $p(id_3) = (24.78, -18.77)$	

Event Calculus in ProbLog



Event Calculus in ProbLog



Markov Logic Networks (MLN)

Syntax: weighted first-order logic formulas (w_i, F_i)

When input events SDE_A **and** SDE_B occur at T,
then the output event CE is initiated:

3.18 $happensAt(SDE_A,\ T) \wedge happensAt(SDE_B,\ T) \Rightarrow initiatedAt(CE,\ T)$

Semantics: (w_i, F_i) represents a probability distribution over possible worlds

SDEs

weight of the i-th formula

$$P(Y{=}\mathbf{y} \mid X{=}\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp\left(\sum_i w_i\, n_i(\mathbf{x},\ \mathbf{y})\right)$$

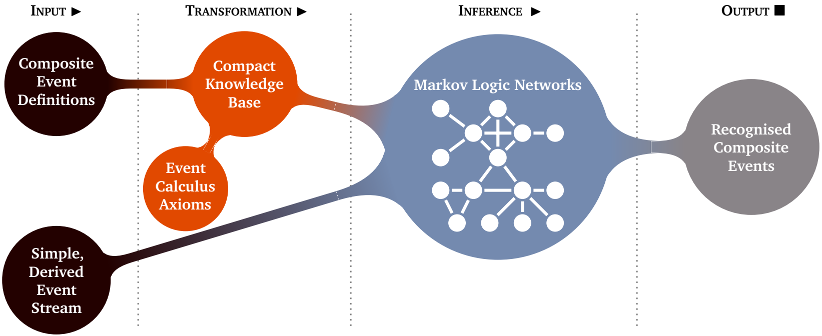
Possible world: CEs

Partition function

number of satisfied groundings

A world violating formulas becomes less probable, but not impossible!

Event Calculus in Markov Logic Networks (MLN-EC)



MLN-EC: Inertia

Marginal Inference:

- For all time points T, calculate the probability of each **CE** being true (recognised), given all **input SDEs** (evidence)

$$P(\texttt{holdsAt}(CE,\ T){=}true \mid SDEs)$$

- Marginal inference is #P-complete $\rightarrow$ approximate inference
- MC-SAT algorithm (Markov Chain Monte Carlo techniques with SAT solver)

MLN-EC: Inertia

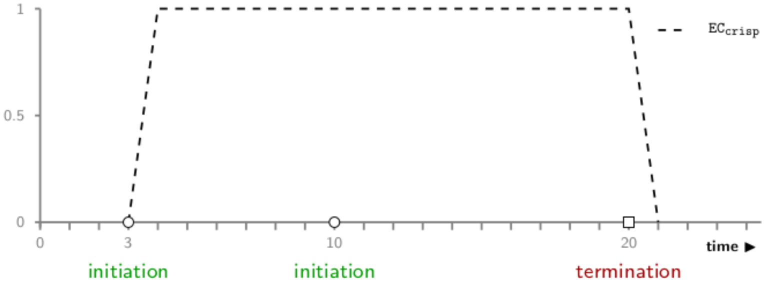
Maximum a Posteriori (MAP) Inference:

- Find the world with the highest probability
- **Input:** truth values for all **input SDEs** (evidence)
- **Output:** truth values of the **output CEs** that maximise the probability (recognition)

$$\underset{\mathtt{holdsAt}(CE,\,T)}{\operatorname{argmax}} \left(P(\mathtt{holdsAt}(CE,\ T) | SDEs) \right)$$

- MAP Inference is NP-hard $\rightarrow$ approximate inference
- Various methods: local search, linear programming, etc.

MLN-EC: Inertia



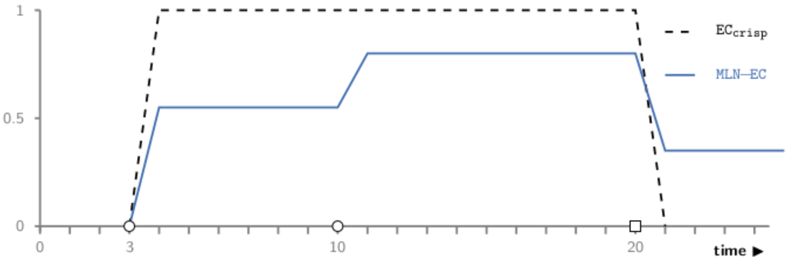
∞ $\text{holdsAt}(CE,\ T{+}1) \Leftarrow$
$\quad [\texttt{Initiation Conditions}]$

∞ $\neg\text{holdsAt}(CE,\ T{+}1) \Leftarrow$
$\quad \neg\text{holdsAt}(CE,\ T) \wedge$
$\quad \neg[\texttt{Initiation Conditions}]$

∞ $\neg\text{holdsAt}(CE,\ T{+}1) \Leftarrow$
$\quad [\texttt{Termination Conditions}]$

∞ $\text{holdsAt}(CE,\ T{+}1) \Leftarrow$
$\quad \text{holdsAt}(CE,\ T) \wedge$
$\quad \neg[\texttt{Termination Conditions}]$

MLN-EC: Inertia



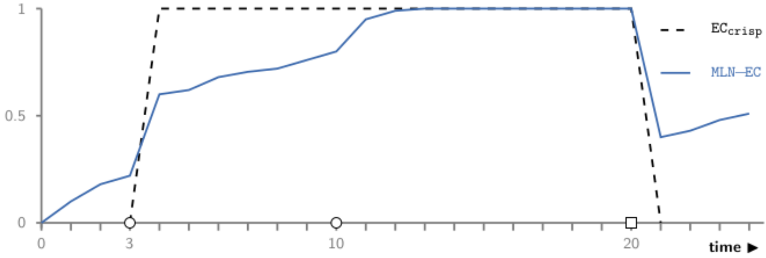
1.2 $\text{holdsAt}(CE,\ T{+}1) \Leftarrow$ [Initiation Conditions]

0.7 $\neg\text{holdsAt}(CE,\ T{+}1) \Leftarrow$ [Termination Conditions]

∞ $\neg\text{holdsAt}(CE,\ T{+}1) \Leftarrow$
$\neg\text{holdsAt}(CE,\ T) \land$
$\neg$[Initiation Conditions]

∞ $\text{holdsAt}(CE,\ T{+}1) \Leftarrow$
$\text{holdsAt}(CE,\ T) \land$
$\neg$[Termination Conditions]

MLN-EC: Inertia



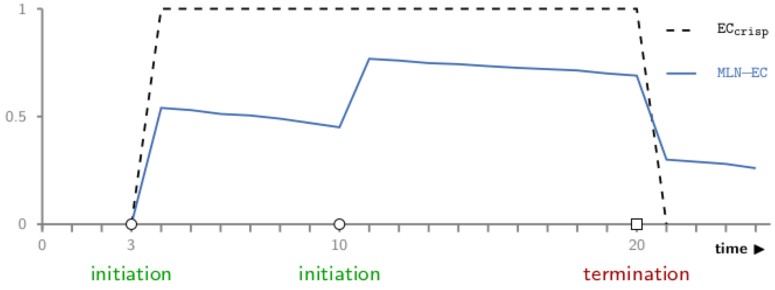
$1.2 \quad \text{holdsAt}(\text{CE},\ \text{T}{+}1) \Leftarrow$
$\quad [\texttt{Initiation Conditions}]$

$0.7 \quad \neg\text{holdsAt}(\text{CE},\ \text{T}{+}1) \Leftarrow$
$\quad [\texttt{Termination Conditions}]$

$2.3 \quad \neg\text{holdsAt}(\text{CE},\ \text{T}{+}1) \Leftarrow$
$\quad \neg\text{holdsAt}(\text{CE},\ \text{T}) \wedge$
$\quad \neg[\texttt{Initiation Conditions}]$

$\infty \quad \text{holdsAt}(\text{CE},\ \text{T}{+}1) \Leftarrow$
$\quad \text{holdsAt}(\text{CE},\ \text{T}) \wedge$
$\quad \neg[\texttt{Termination Conditions}]$

MLN-EC: Inertia



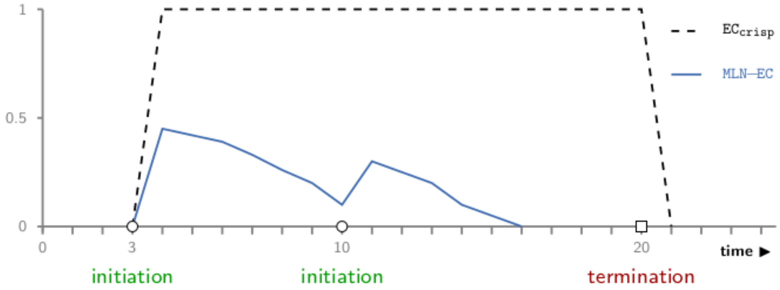
$1.2 \quad holdsAt(CE,\ T{+}1) \Leftarrow$
$\quad\quad [\texttt{Initiation Conditions}]$

$\infty \quad \neg holdsAt(CE,\ T{+}1) \Leftarrow$
$\quad\quad \neg holdsAt(CE,\ T) \land$
$\quad\quad \neg [\texttt{Initiation Conditions}]$

$0.7 \quad \neg holdsAt(CE,\ T{+}1) \Leftarrow$
$\quad\quad [\texttt{Termination Conditions}]$

$2.3 \quad holdsAt(CE,\ T{+}1) \Leftarrow$
$\quad\quad holdsAt(CE,\ T) \land$
$\quad\quad \neg [\texttt{Termination Conditions}]$

MLN-EC: Inertia



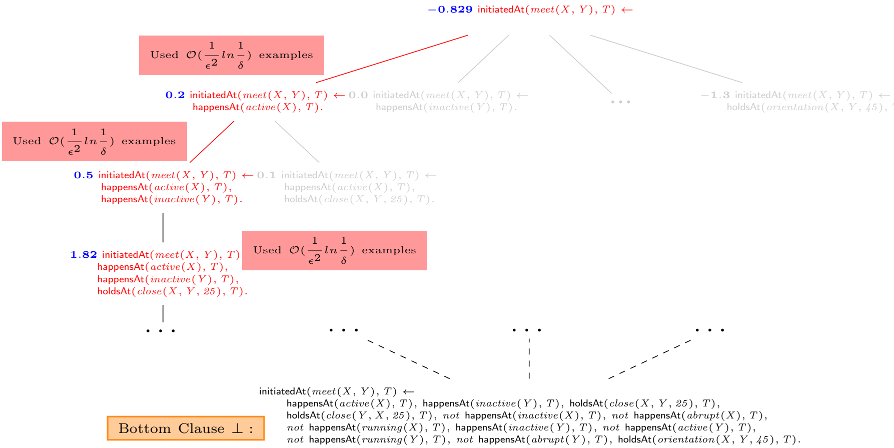
1.2 holdsAt(CE, T+1)⇐
[Initiation Conditions]

∞ ¬holdsAt(CE, T+1)⇐
¬holdsAt(CE, T) ∧
¬[Initiation Conditions]

0.7 ¬holdsAt(CE, T+1)⇐
[Termination Conditions]

0.6 holdsAt(CE, T+1)⇐
holdsAt(CE, T) ∧
¬[Termination Conditions]

Online Structure & Weight Learning in MLN



- Simultaneous structure & weight learning.
- Weight learning with AdaGrad.

The AdaGrad Weight Update Rule

Previous weight of the i-th rule

Learning rate

Rule's current mistakes

Regularization rate

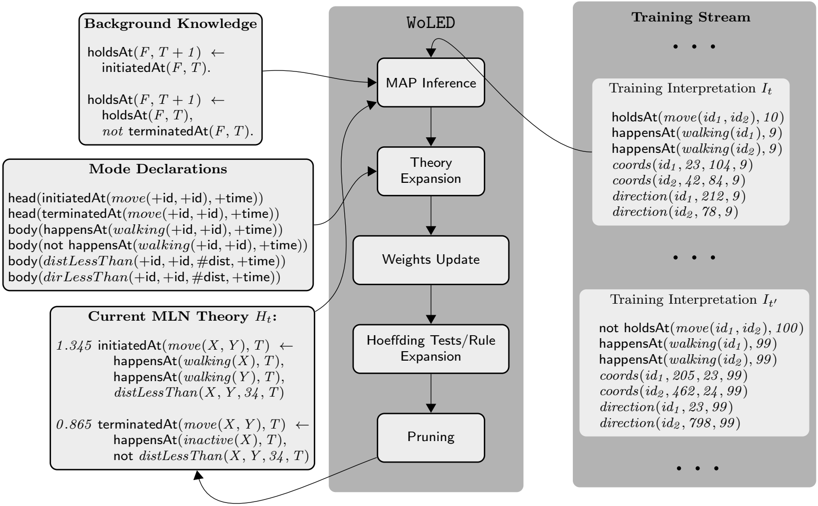
$$w_i^{t+1} = sign(w_i^t - \frac{\eta}{C_i^t}\Delta g_i^t)\ max\{0, |w_i^t - \frac{\eta}{C_i^t}\Delta g_i^t| - \lambda\frac{\eta}{C_i^t}\}$$

Current weight of the i-th rule

Term proportional to the rule's accumulated past mistakes

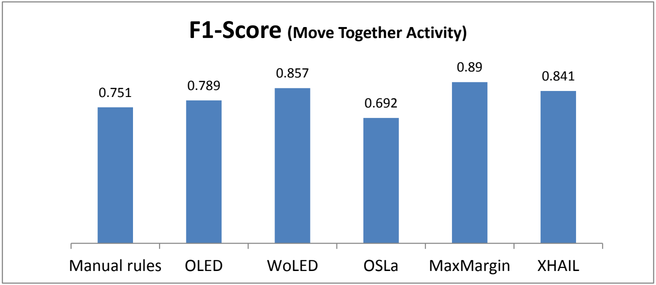
- Δg_i^t (i-th rule's mistakes at time t): difference in rule's true groundings in the true state and the MAP-inferred state.

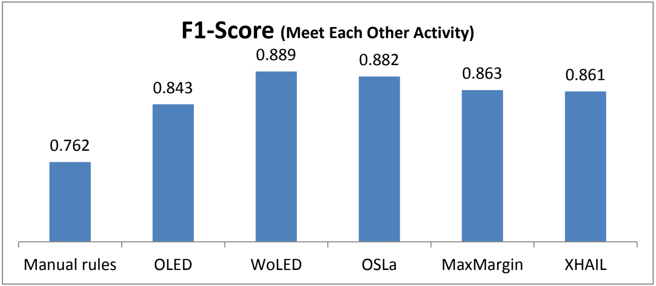
OLED-MLN



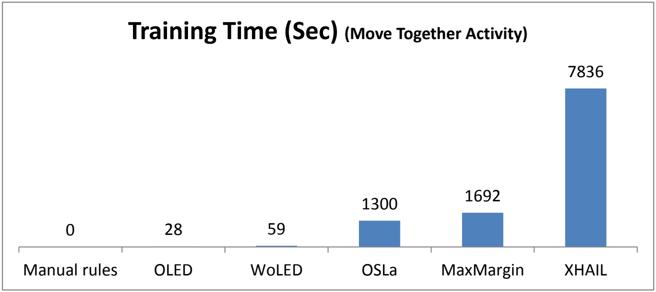
Background Knowledge
holdsAt(F, $T+1$) $\leftarrow$
initiatedAt(F, T).
holdsAt(F, $T+1$) $\leftarrow$
holdsAt(F, T),
not terminatedAt(F, T).
Mode Declarations
head(initiatedAt($move$(+id, +id), +time))
head(terminatedAt($move$(+id, +id), +time))
body(happensAt($walking$(+id, +id), +time))
body(not happensAt($walking$(+id, +id), +time))
body($distLessThan$(+id, +id, #dist, +time))
body($dirLessThan$(+id, +id, #dist, +time))
Current MLN Theory H_t:
1.345 initiatedAt($move(X, Y)$, T) $\leftarrow$
happensAt($walking(X)$, T),
happensAt($walking(Y)$, T),
$distLessThan(X, Y, 34, T)$
0.865 terminatedAt($move(X, Y)$, T) $\leftarrow$
happensAt($inactive(X)$, T),
not $distLessThan(X, Y, 34, T)$
WoLED
MAP Inference
Theory Expansion
Weights Update
Hoeffding Tests/Rule Expansion
Pruning
Training Stream
. . .
Training Interpretation I_t
holdsAt($move(id_1, id_2)$, 10)
happensAt($walking(id_1)$, 9)
happensAt($walking(id_2)$, 9)
$coords(id_1, 23, 104, 9)$
$coords(id_2, 42, 84, 9)$
$direction(id_1, 212, 9)$
$direction(id_2, 78, 9)$
. . .
Training Interpretation $I_{t'}$
not holdsAt($move(id_1, id_2)$, 100)
happensAt($walking(id_1)$, 99)
happensAt($walking(id_2)$, 99)
$coords(id_1, 205, 23, 99)$
$coords(id_2, 462, 24, 99)$
$direction(id_1, 23, 99)$
$direction(id_2, 798, 99)$
. . .

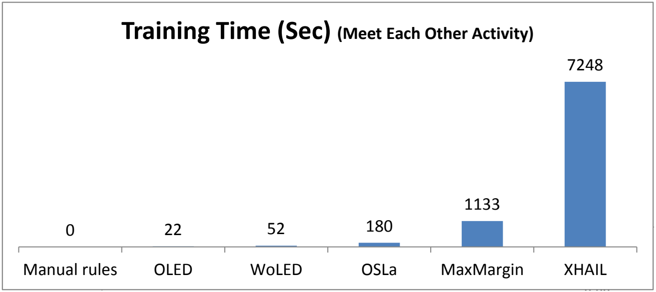
OLED-MLN Evaluation on the CAVIAR Dataset





OLED-MLN Evaluation on the CAVIAR Dataset





Some Useful Reading Readings

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- Event Calculus in ProbLog:
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