Learning First-Order Temporal Logic Formulas

Alan Fern and Robert Givan

Electrical and Computer Engineering Purdue University

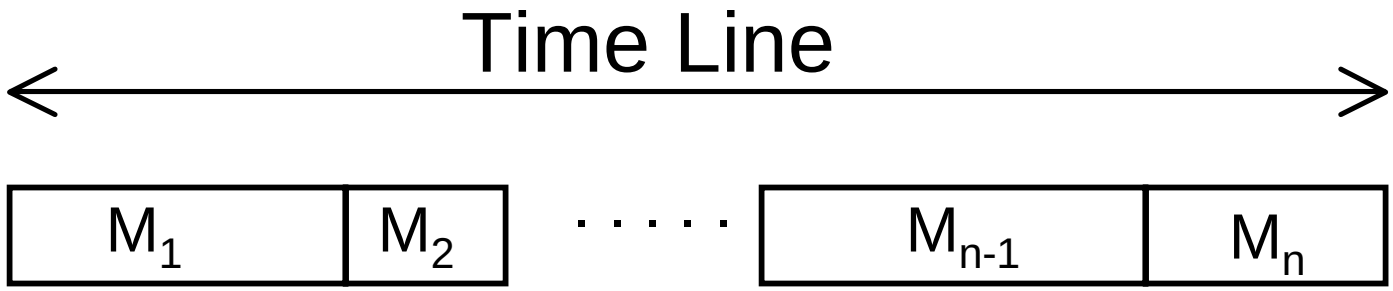
Overview

- **Temporal Logic**
- **Motivation**
  - Learning Visual Event Definitions
  - Learning Control Knowledge for Planners
  - Relational Reinforcement Learning
- **Related ML Techniques**
  - Propositional sequence mining
  - Explicit and propositional FSA/HMM inference
  - Inductive Logic Programming

Temporal Models

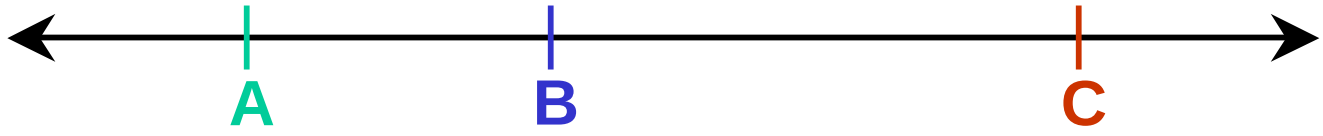
Linear temporal model: a sequence of atemporal models.

Atemporal model: a traditional first-order or propositional model.



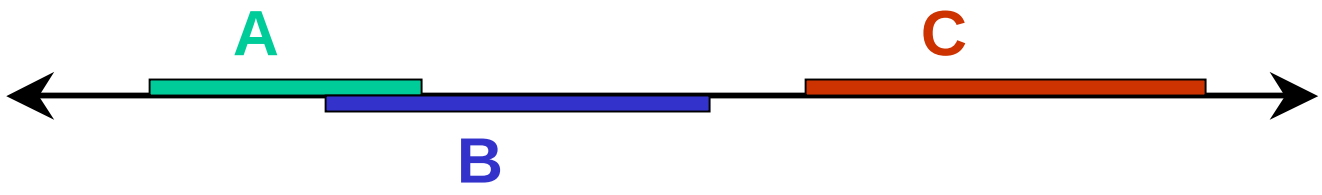
Time-points vs. Time-intervals

Time-point semantics



(A *before* **B)** ***AND*** **(B** *before* **C)**

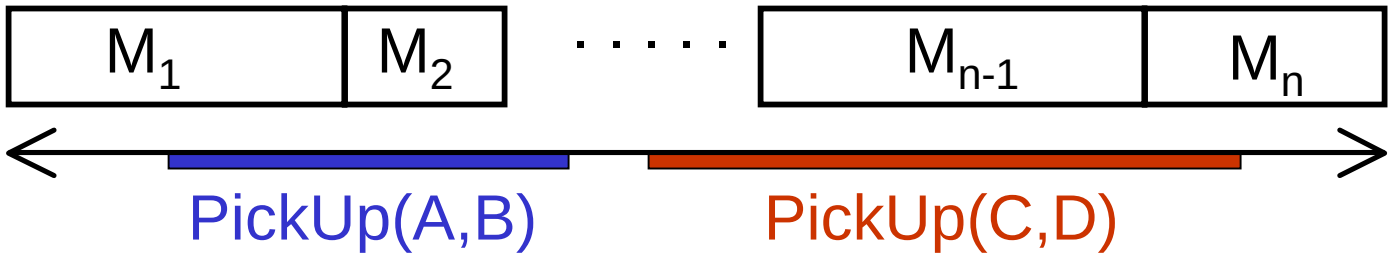
Time-interval semantics (Allen, 1983)



(**A** *overlaps* **B**) *before* **C**

Typical Learning Scenario

Given: a linear temporal model and
a set of intervals labeled by events.

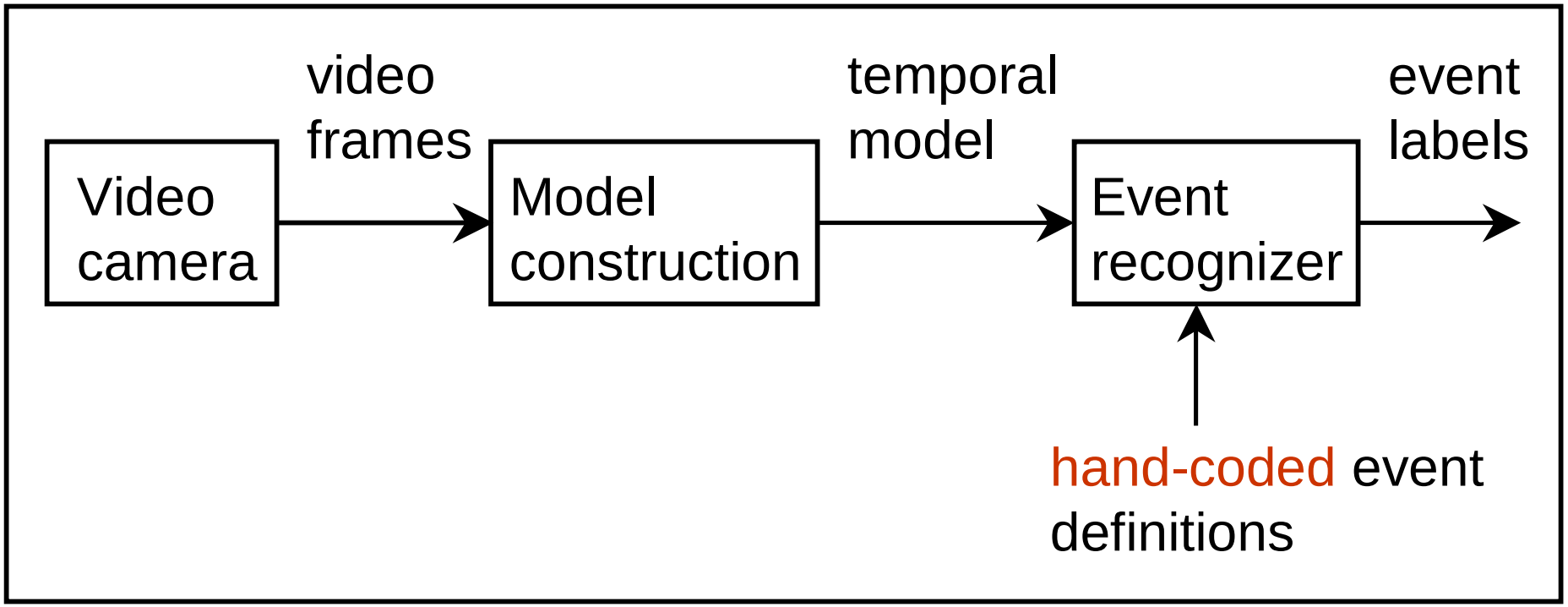


Output: a temporal logic formula *E* defining
the events in the training set.

$$\mathrm{PickUp}(x, y) \equiv E(x, y)$$

Visual Event Recognition

The LEONARD system (Siskind. to appear in JAIR)



Example event label: PUT(A,B)@I Agent A put down object B during time interval I.

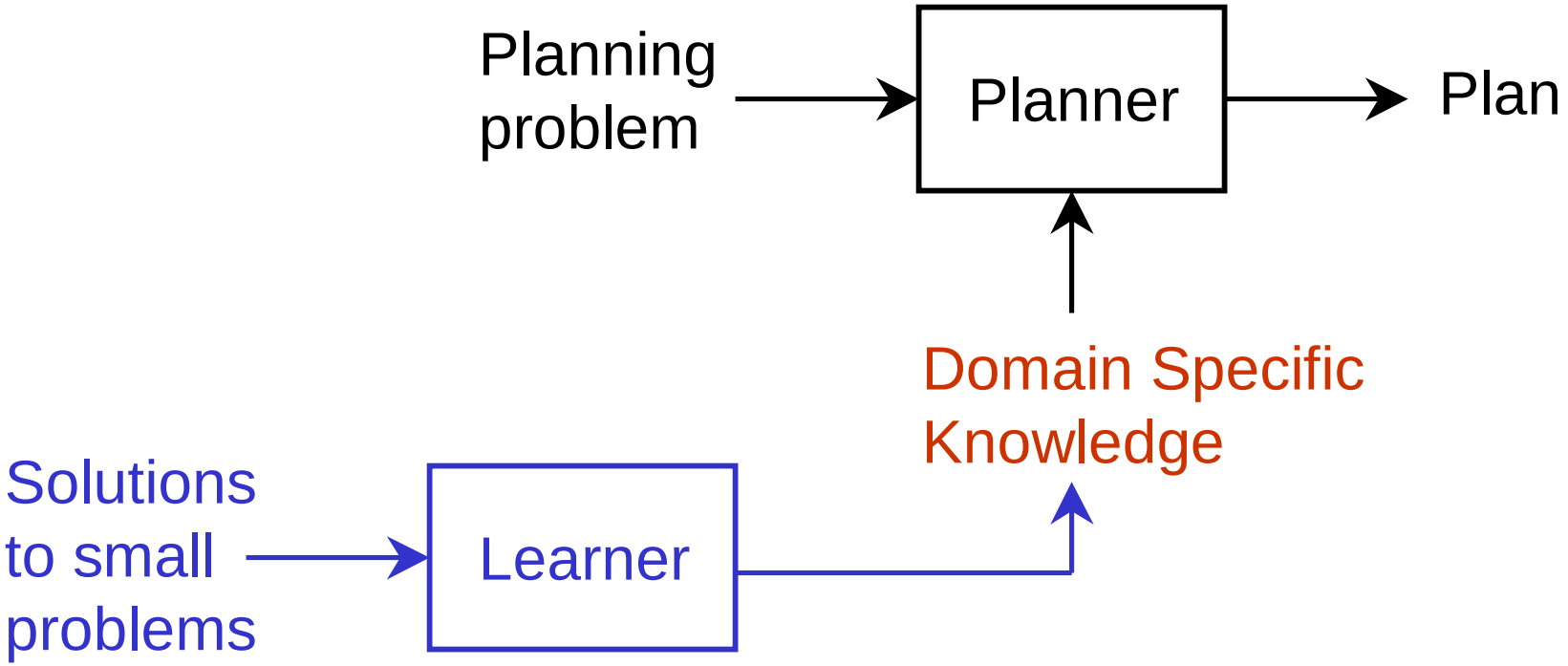
Visual Event Characteristics

- **First-Order Structure** — there are objects and relations among them.
- **Temporal Structure** — there are relation-ships among time-intervals.
- **Hierarchical Structure** — events are composed of related sub-events.

Example Event-Logic Formula

$$Put(x, y) \equiv$$
$$\left[\text{attached}(x, y) \wedge \text{supports}(x, y)\right]$$
$$\wedge_{meets}$$
$$(\exists z)\left[z \neq x \wedge \text{supports}(z, y)\right]$$

Learning Temporal Logic Formulas for Planning



Example Domain Knowledge: Don't move blocks that are 'solved'.

Learning Declarative Control Rules

- (Huang, Selman & Kautz. ICML'00) learn control rules from examples of optimal plans for simple problems.

Policy Constraints:

$$\text{Antecedent}(X) \rightarrow \text{action}(X)$$

$$\text{Antecedent}(X) \rightarrow \neg\text{action}(X)$$

Research Direction: Learn general FO temporal logic formulas in the spirit of TL-Plan (Bacchus & Kabanza. AIJ'00).

- Allow for state constraints in rule heads.
- Allow for temporal constraints in rule bodies.
- Constrain the strategy/program rather than the policy.

Relational Reinforcement Learning

- Learning HAMs, options, macros in relational domains
- **Approach:** initially consider deterministic goal-based domains, as in

  (Dzeroski, De Raedt, & Driessens. MLJ'01)

Related ML Techniques

- Mining propositional time-point patterns

  (Mannila & Toivonen. KDD'95)
  (Agrawal & Srikant. ICDE'95)
- Mining propositional time-interval patterns

  (Cohen, P. 2001) (Kam & Fu 2000)
  (Rainsford & Roddick 1999)
- FSM/HMM Induction
- Inductive Logic Programming

References

Agrawal, R., & Srikant, R. (1995). Mining Sequential Patterns. *International Conference on Data Engineering.*

Allen, J. (1983). Maintaining Knowledge about Temporal Intervals. *Communications of the ACM*. (26),11.

Bacchus, F., & Kabanza, F. (2000). Using Temporal Logics to Express Search Control Knowledge for Planning. *Artificial Intelligence* (16).

Cohen, P. (2001). Fluent Learning: Elucidation the Structure of Episodes. *Symposium on Intelligent Data Analysis*.

Dzeroski, S., De Raedt, L., & Driessens, K. (2001). Relational Reinforcement Learning. *Machine Learning* (42).

Huang, Y., Selman, B., & Kautz, H. (2000). Learning Declarative Control Rules for Constraint-Based Planning. *International Conference on Machine Learning*.

Kam, P., & Fu, A. (2000). Discovering Temporal Patterns for Interval-Based Events. *International Conference on Data Warehousing and Knowledge Discovery*.

Mannila, H., & Toivonen, H. (1995). Discovering Frequent Episodes in Sequences. *International Conference on Knowledge Discovery and Data Mining*.

Rainsford, C., & Roddick, J. (2000). Temporal Interval Logic in Data Mining. *Pacific Rim International Conference on Artificial Intelligence*.

Siskind, J. (to appear). Grounding the Lexical Semantics of Verbs in Visual Perception Using Force Dynamics and Event Logic. *Journal of Artificial Intelligence Research.*