

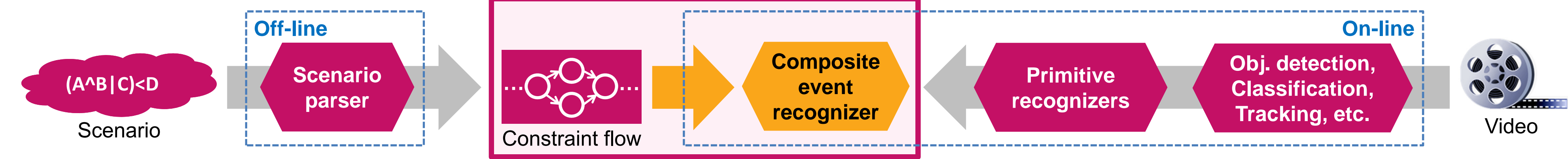
Scenario-Based Video Event Recognition by Constraint Flow

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Introduction

Scenario-based video event recognition

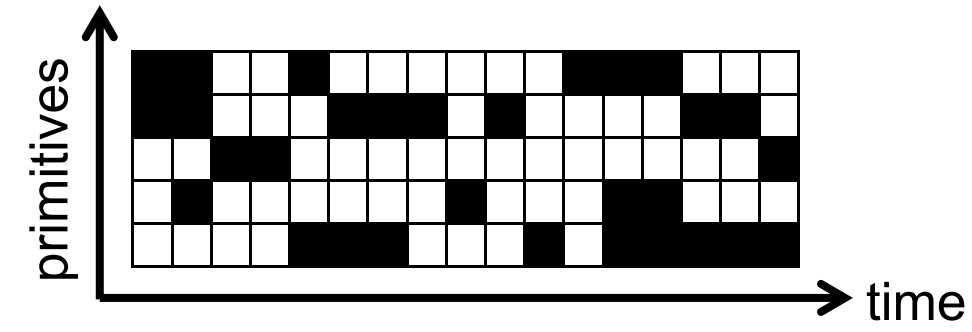
Recognizing events in videos with given knowledge (*scenario*) about how they happen.

Contributions

- An easy and flexible scenario description method
- Online and exact inference of events without heuristics

Goal & Challenge

Search for the best video interpretation



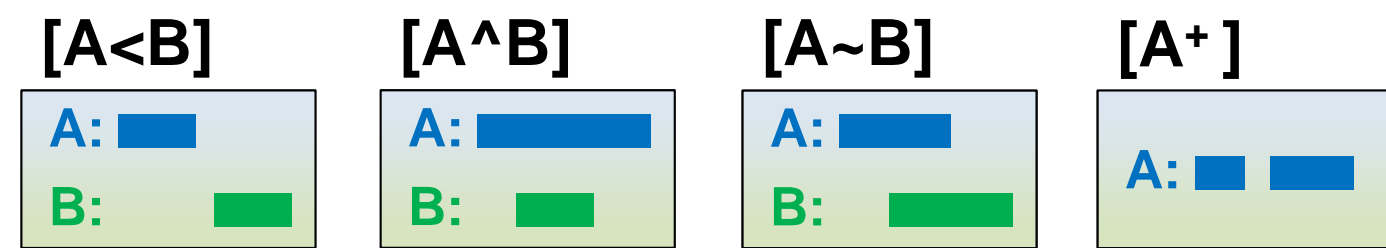
A video interpretation = a binary matrix indicating occurrences of primitives over time

- The number of interpretations increases exponentially over time \rightarrow which one is **feasible** and **optimal**?
- We search the best interpretation by dynamic programming with **constraint flow**.

Scenario Description Method

A *scenario* = a set of temporal-logical **constraints** for the arrangements of time intervals of primitives

Temporal relationships (<, ^, ~, +)



Logical relationships (&, |)

- [A & B]**: both of A and B occur (no temporal ordering).
- [A | B]**: only one of A and B occurs.

Dummy element (#)

Parentheses

- Precedence (parentheses > logical > temporal)
- Hierarchical description

Constraint Flow

A dynamic configuration of scenario constraints

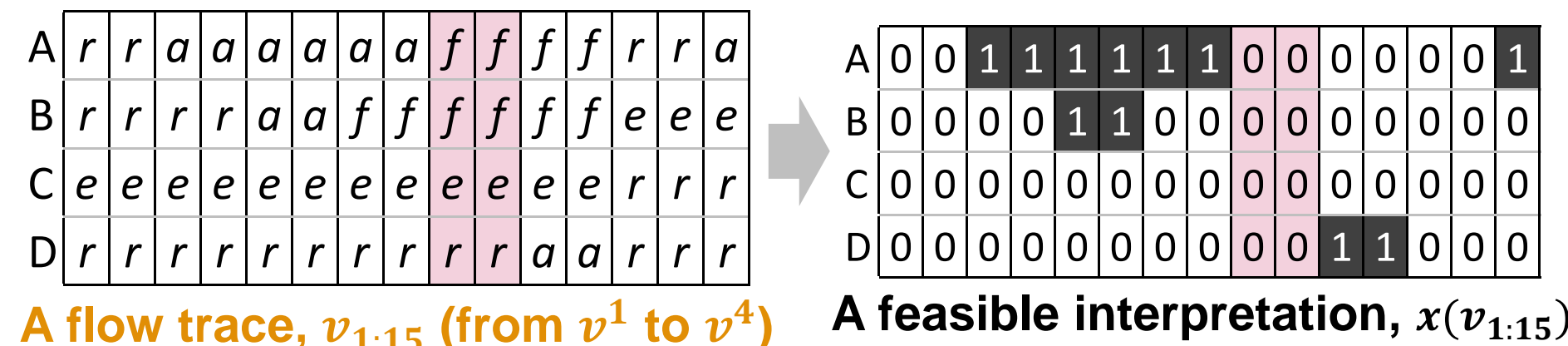
- Transitions (edges) among combinatorial states (vertices)
- Feasible interpretations must follow the constraint flow!

Automatic construction of constraint flow

- Breadth-first **search** and **generation** of flow vertices

Recognition with Constraint Flow

Flow tracing to generate feasible interpretations



Score function for traces

- Observation agreement & Penalty for idle intervals

$$f(v_{1:t}) = p(x(v_{1:t}) | O_{1:t}) \cdot B(v_{1:t})$$

$$\propto p(O_t | x(v_t)) \cdot \exp(-\beta I_b(v_t)) \cdot f(v_{1:t-1})$$

Online, exact inference on a bounded search space

- Optimization by dynamic programming

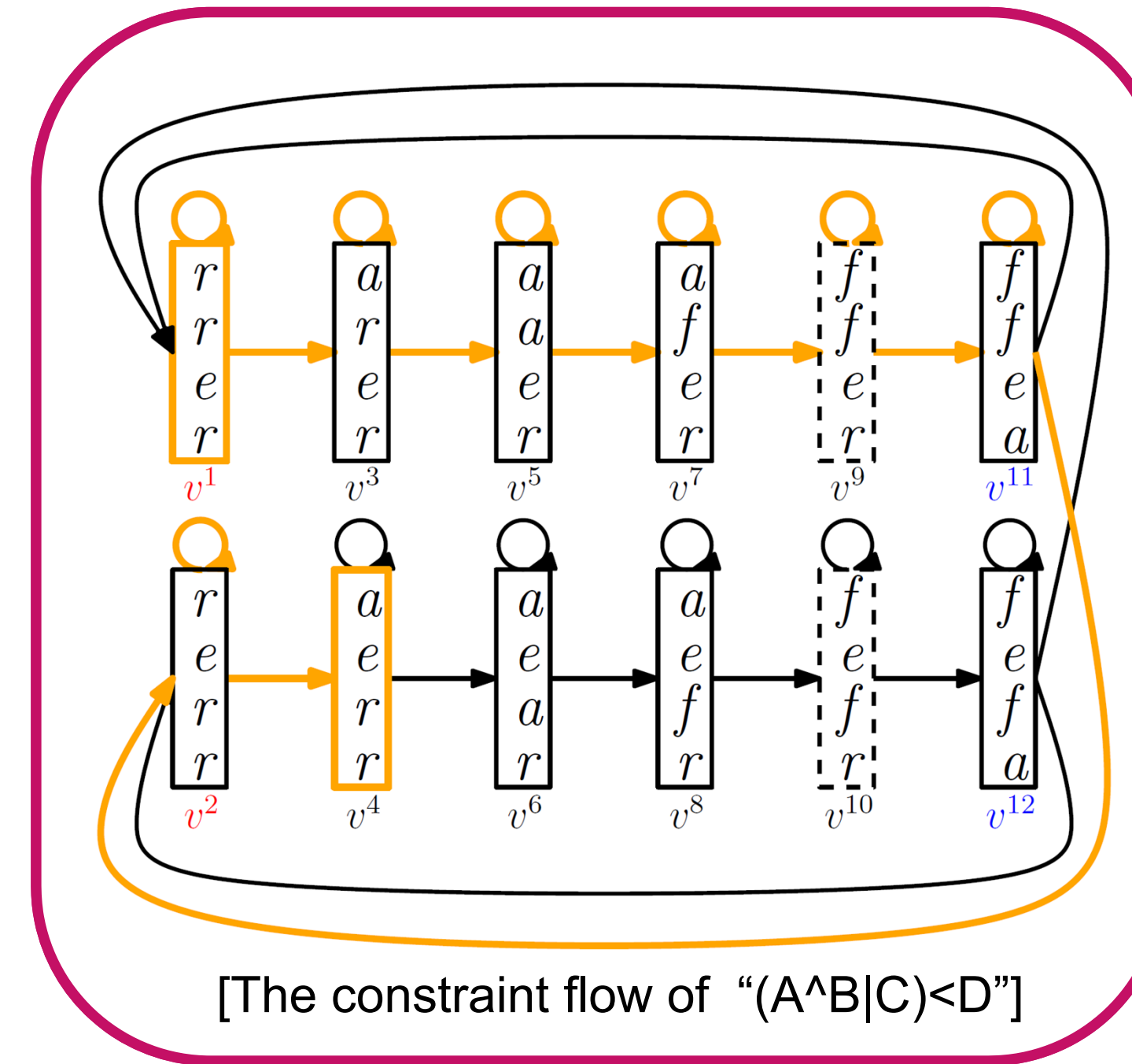
$$\max_{v_{1:t-1}} f([v_{1:t-1}, v_t = v^k]) \propto \exp(-\beta I_b(v^k)) \cdot p(O_t | x(v^k)) \cdot \max_{v_{t-1}} \left\{ \max_{v_{1:t-2}} f([v_{1:t-2}, v_{t-1}]) \right\}$$

- Keeping only one best interpretation per each flow node is sufficient to track the globally optimal solution.

$$V_t(v^k) = \left[\arg \max_{v_{1:t-1}} f([v_{1:t-1}, v_t = v^k]), v_t = v^k \right]$$

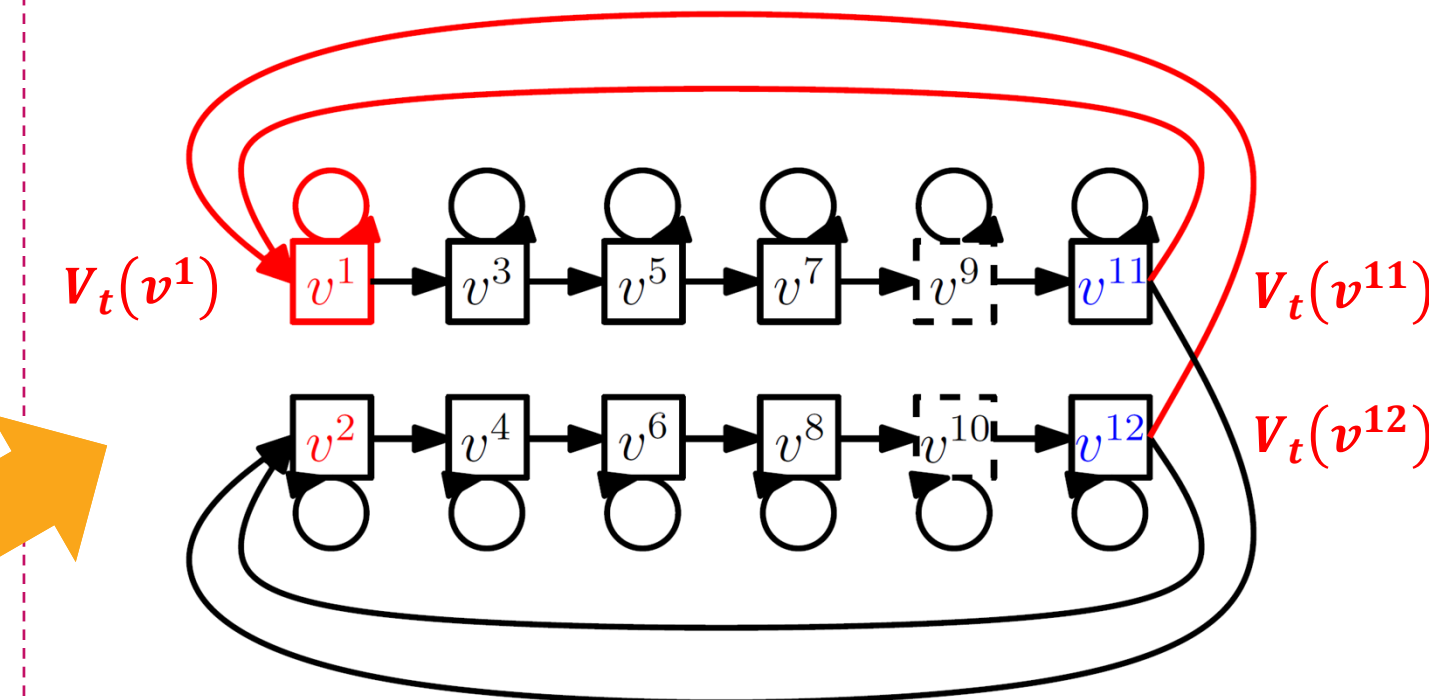
$$\hat{X}_t = x(\arg \max_{v_{1:t}} f(v_{1:t})) = x(\arg \max_{V_t(v^k)} f(V_t(v^k)))$$

- The size of the search space is not a parameter anymore, but **bounded by the number of flow vertices**.



Recognition Example

- $\{V_t(v^k)\}_{k=1}^{12}$ and $\{f(V_t(v^k))\}_{k=1}^{12}$ are given.



- 3 incoming traces for v^1 at time $t+1$:

$$\left. \begin{array}{l} \text{From } v^1: [V_t(v^1), v^1] \\ \text{From } v^{11}: [V_t(v^{11}), v^1] \\ \text{From } v^{12}: [V_t(v^{12}), v^1] \end{array} \right\} \text{Select the best one among them for } V_{t+1}(v^1)$$

- Calculate $f(V_{t+1}(v^1))$ using own observation likelihood and the idle penalty.
- Do the same for the remainders, $\{V_{t+1}(v^k)\}_{k=2}^{12}$

Experiments

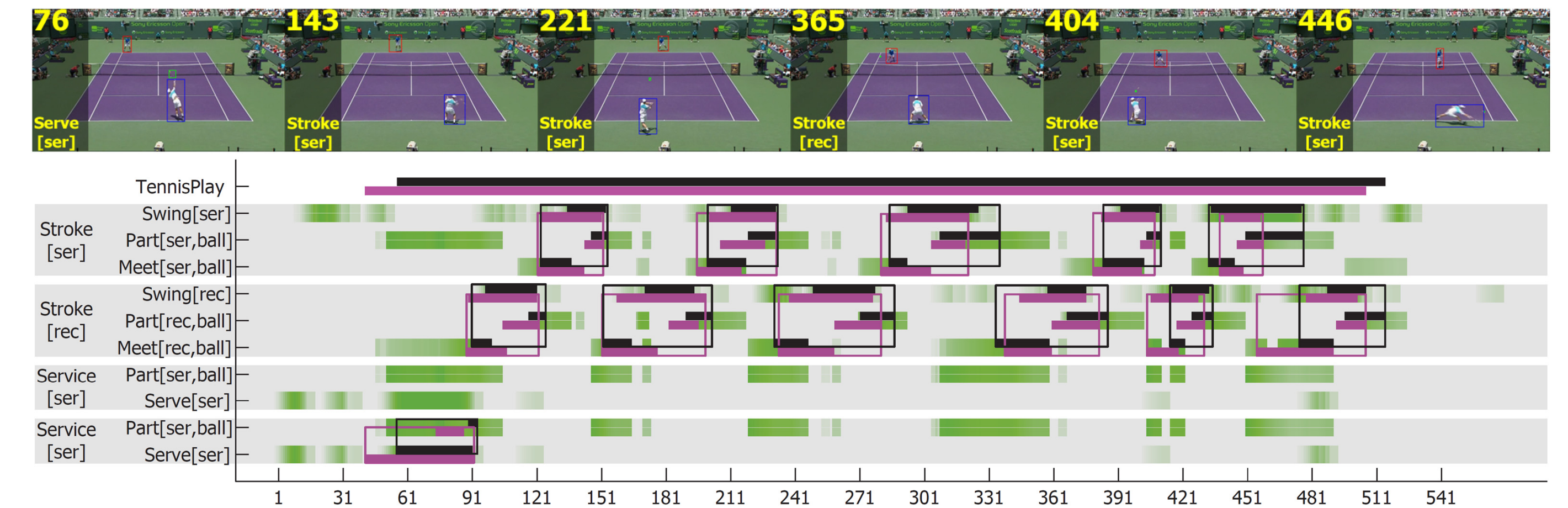
Surveillance sequence

- 8 target events (transactions) in a sequence, 476 flow vertices (precision: 0.90, FPR: 0.0053)



Tennis sequence

- With action recognizers [Tran et al., ECCV'08], 266 flow vertices (precision: 0.69, FPR 0.033)



Conclusion

- A new scenario description method
- Exact inference, which guarantees the optimal solution, via **constraint flow**

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