

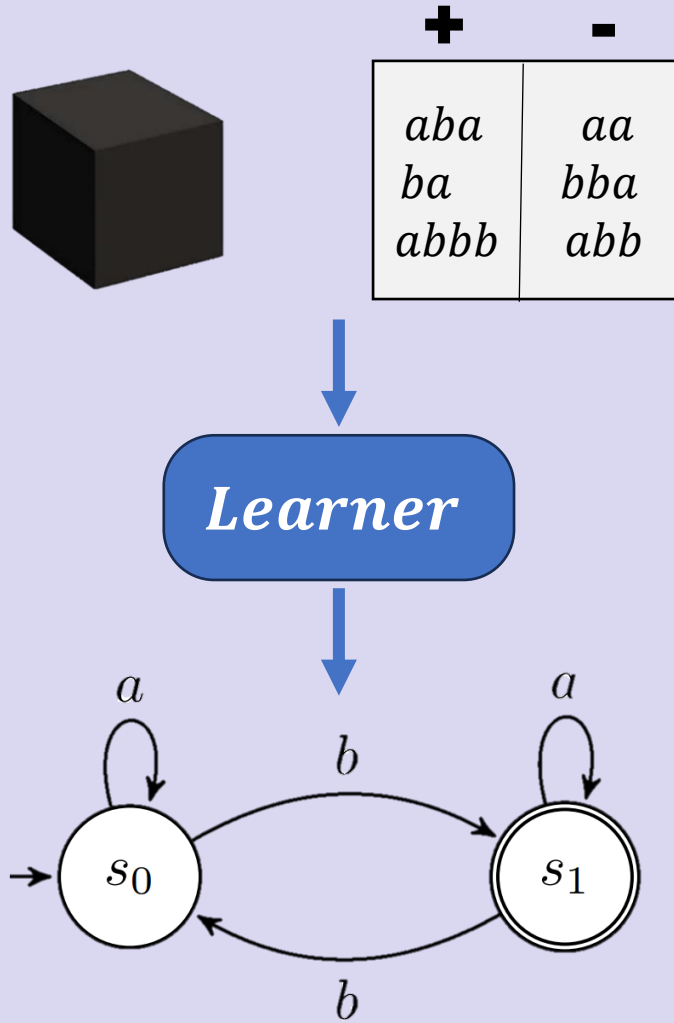
Learning Broadcast Protocols (with LeoParDS)

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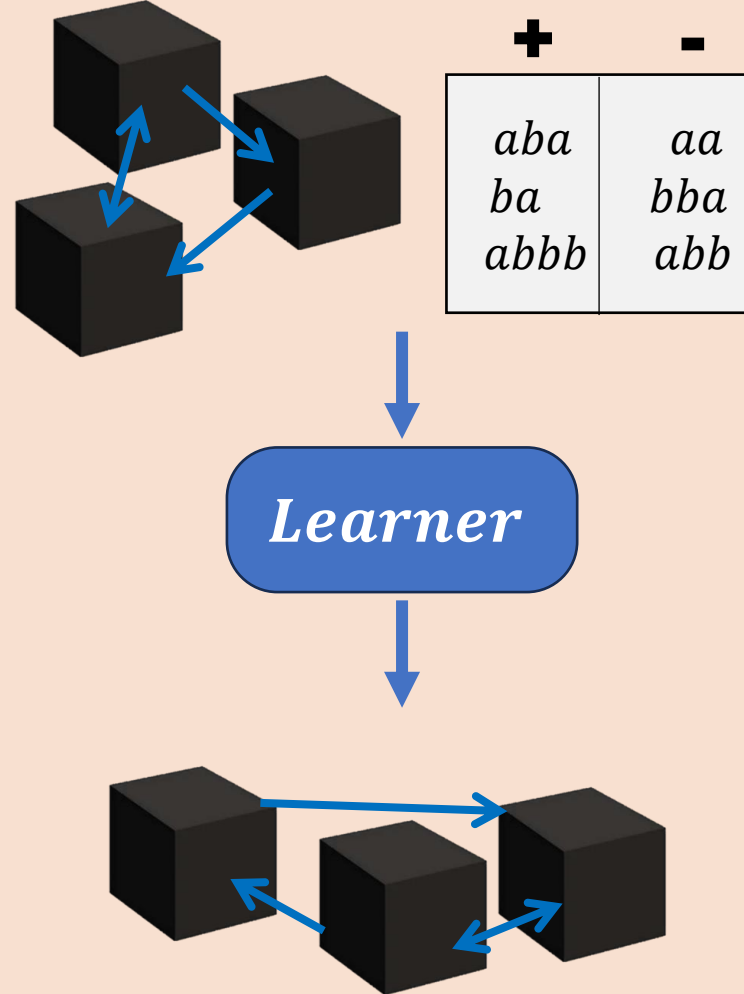
²CISPA Helmholtz Center for Information Security

Automata Learning

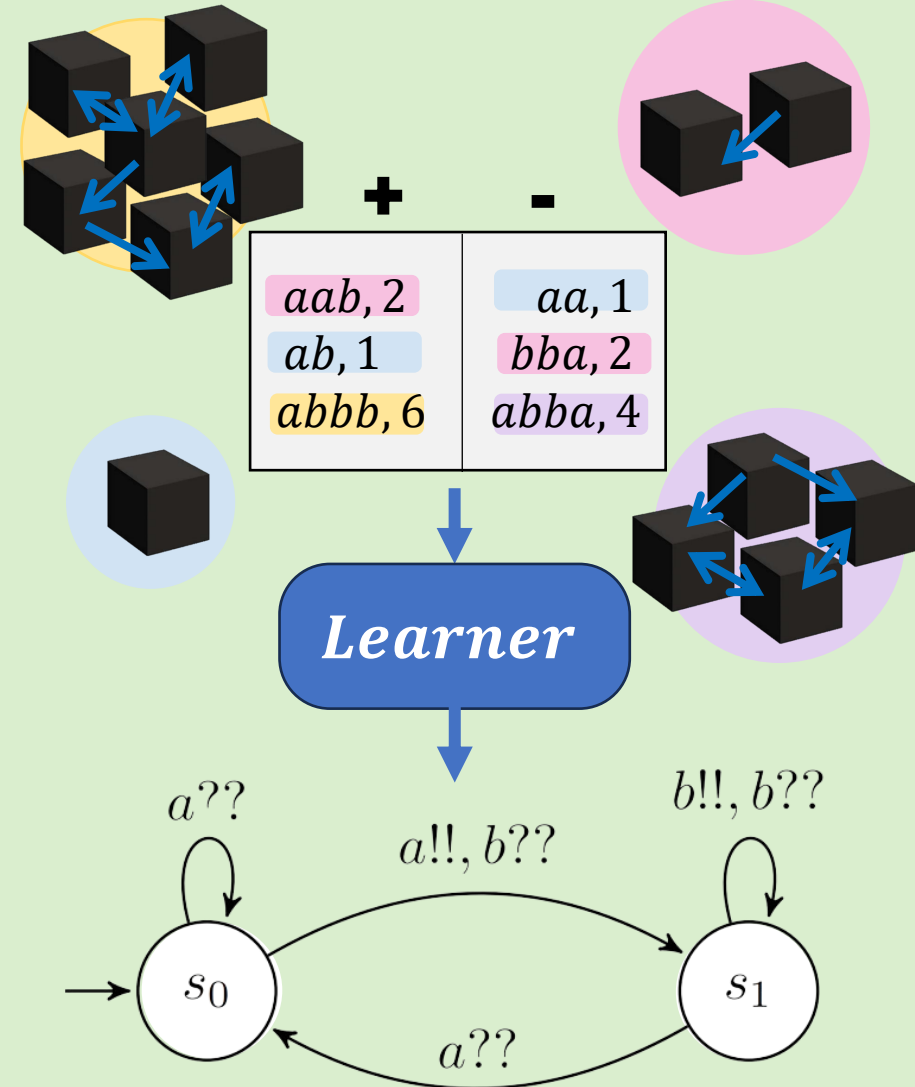


Learning Concurrent systems

Fixed size
(state of the art)



Arbitrary size
Learning Broadcast Protocols, AAAI24



Parametrized protocols

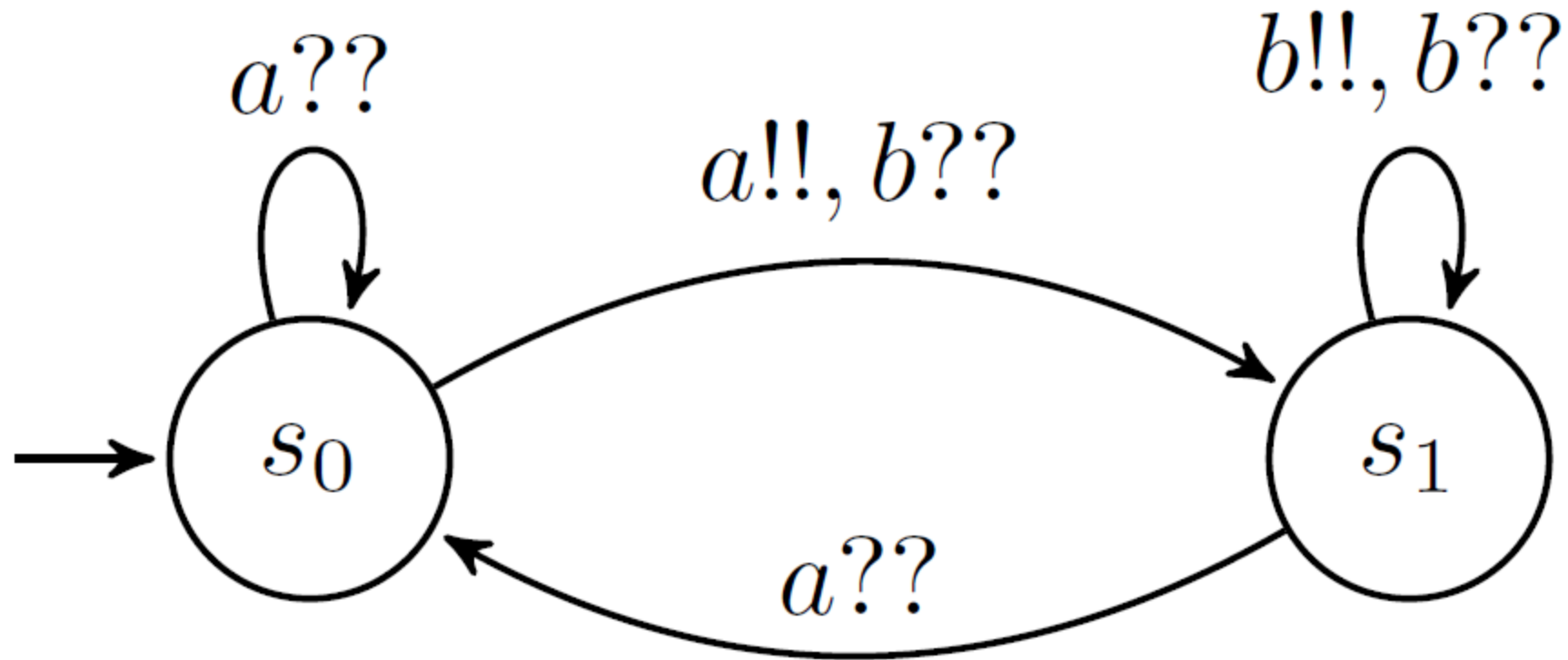
Given a protocol P , $n \in \mathbb{N}$.

A parallel running of protocol P for n processes: $P^n = \underbrace{P \parallel P \parallel \dots \parallel P}_n$

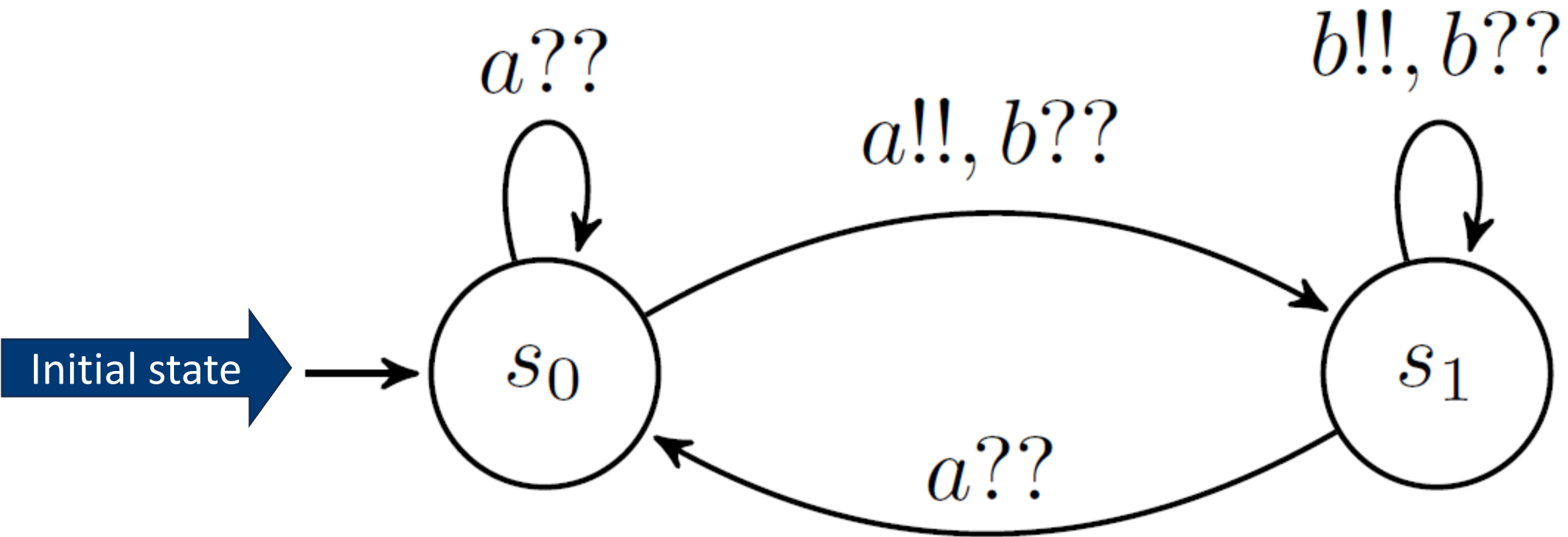
The “language” of P^n : $\mathcal{L}(P^n) = \underbrace{P \parallel P \parallel \dots \parallel P}_n$

The “language” of a protocol P : $\mathcal{L}(P) = \bigcup_{n \in \mathbb{N}} \mathcal{L}(P^n)$

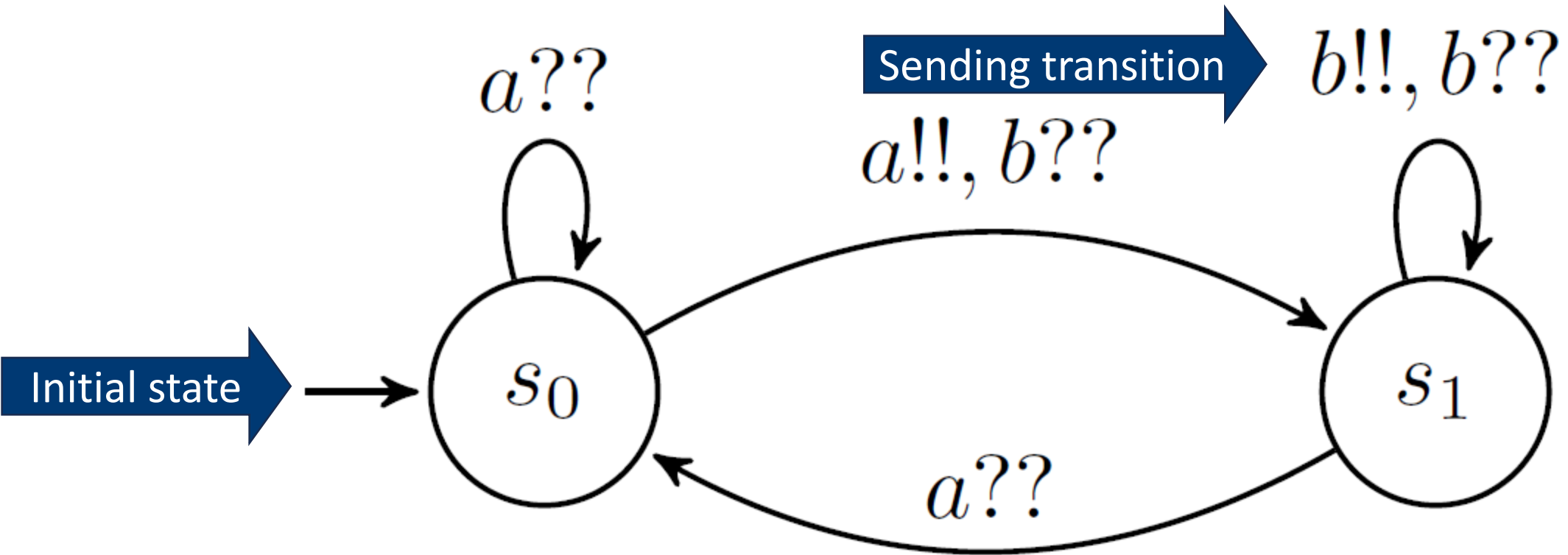
A Broadcast Protocol (BP)



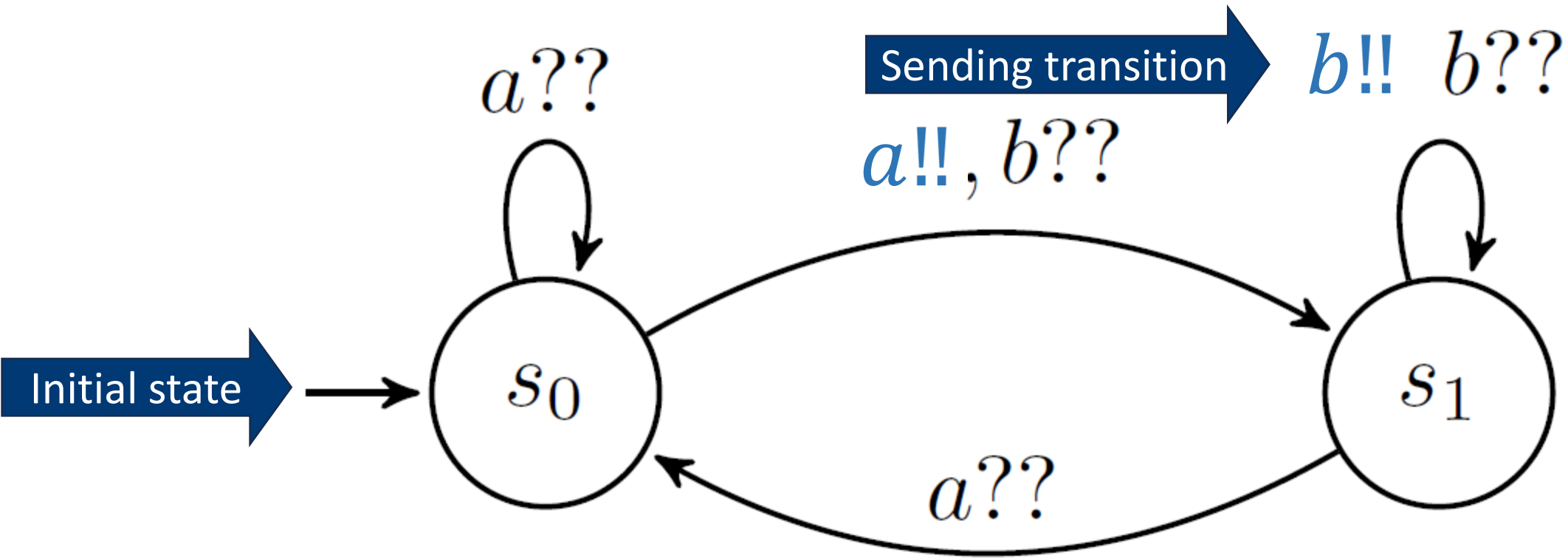
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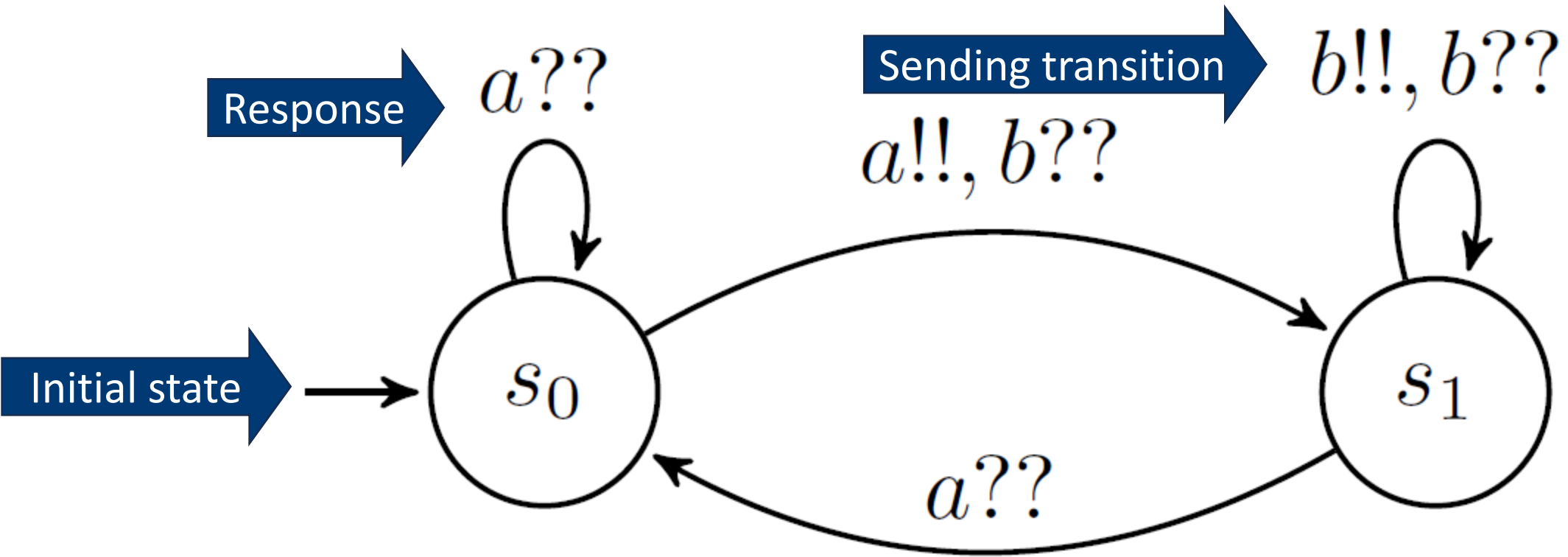
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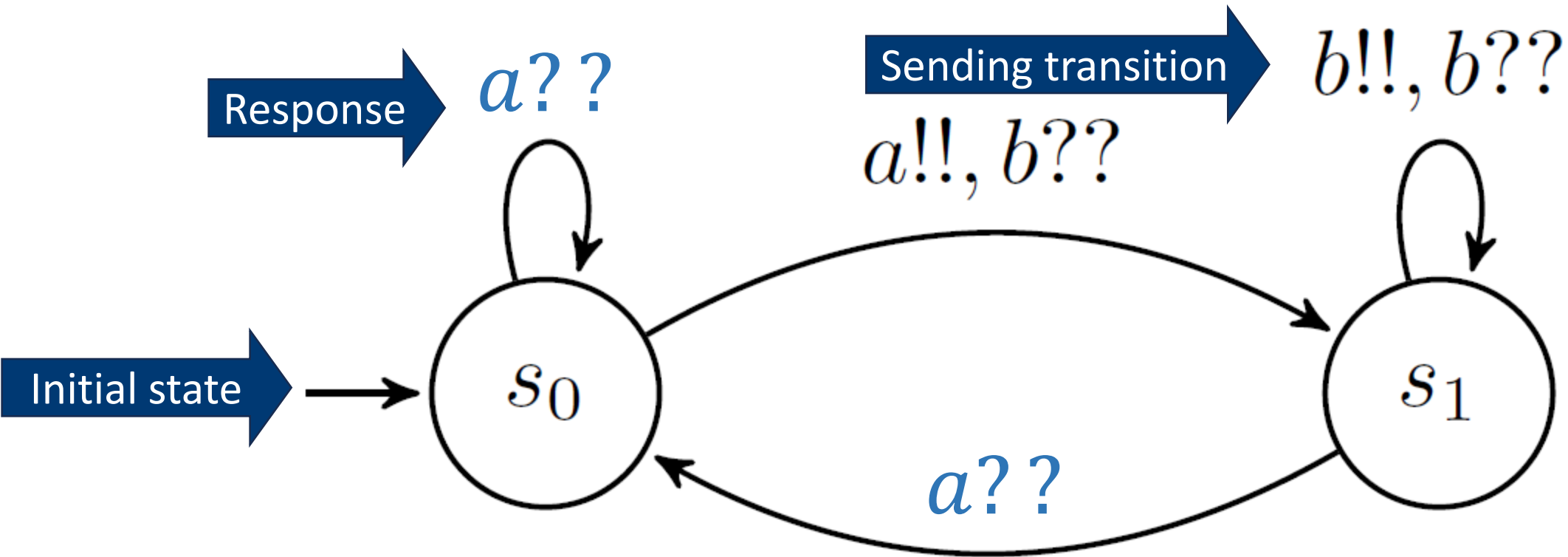
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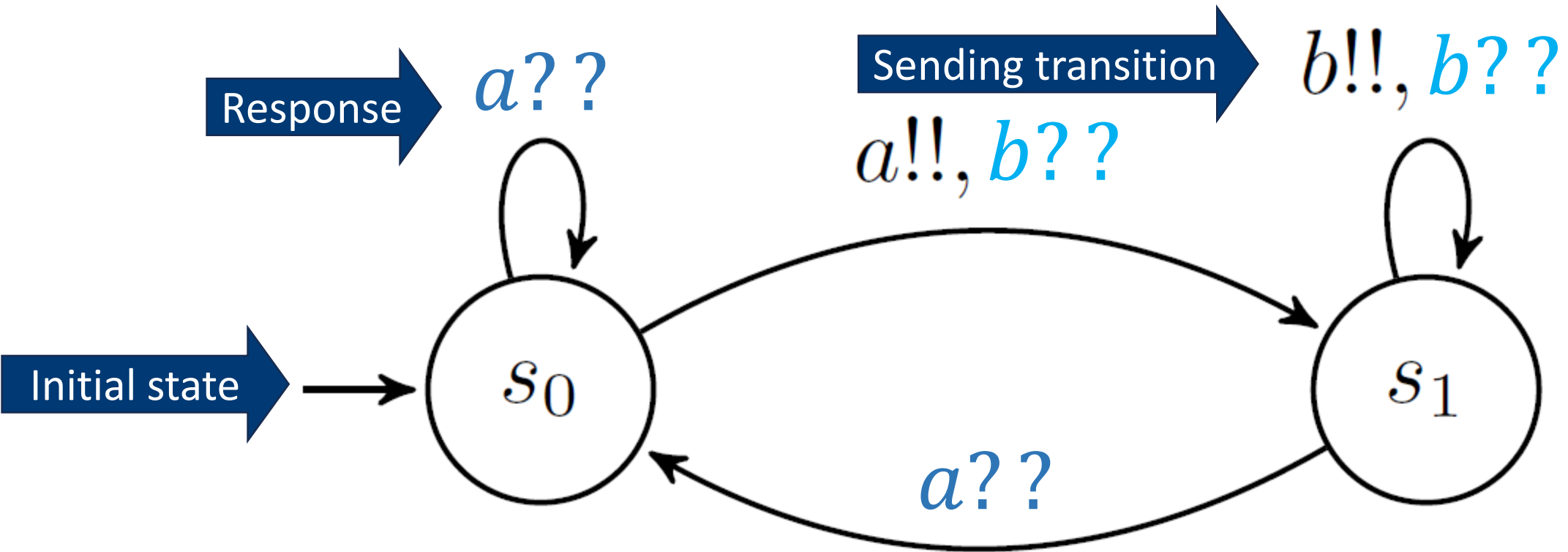
A Broadcast Protocol (BP)



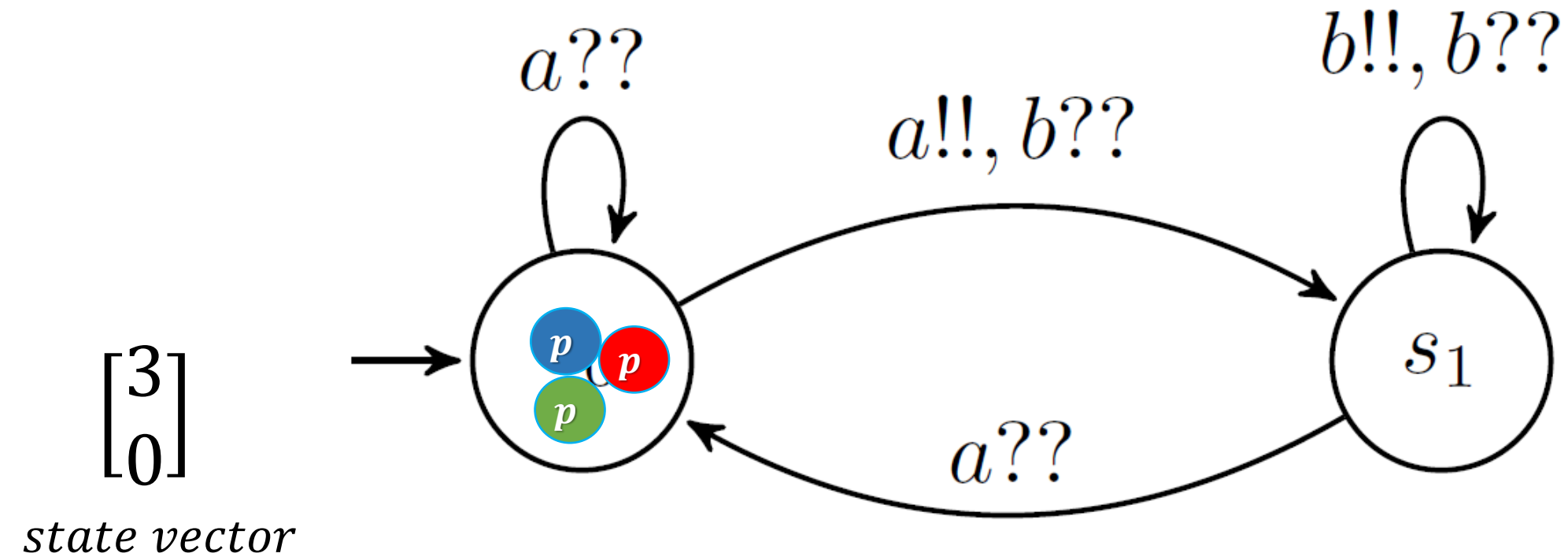
A Broadcast Protocol (BP)



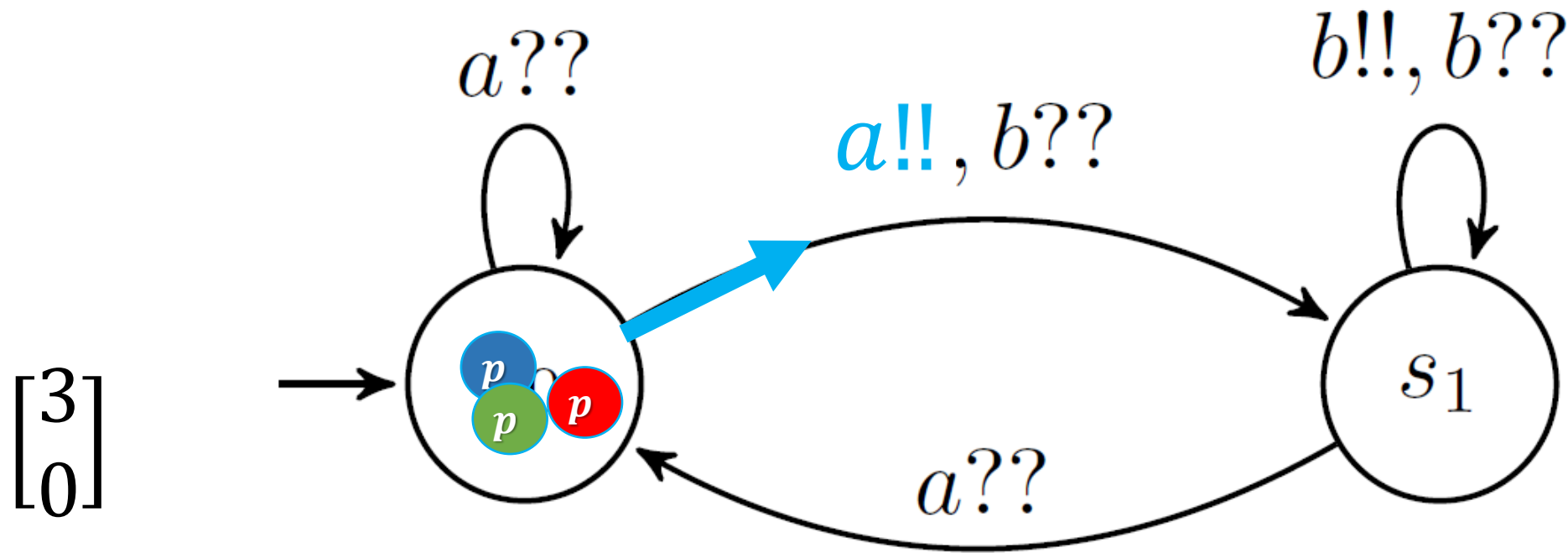
A Broadcast Protocol (BP)



A simple BP and its execution



A simple BP and its execution

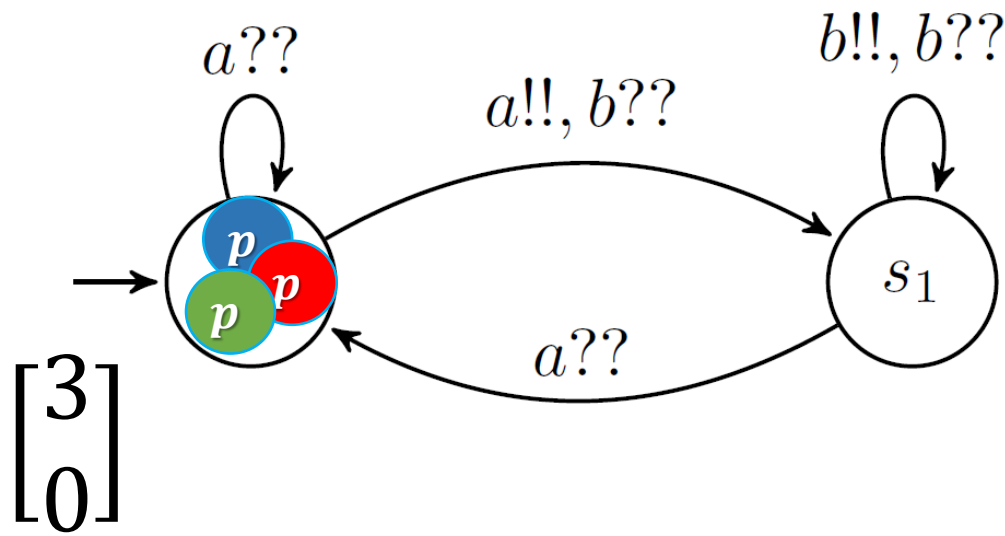


state vector

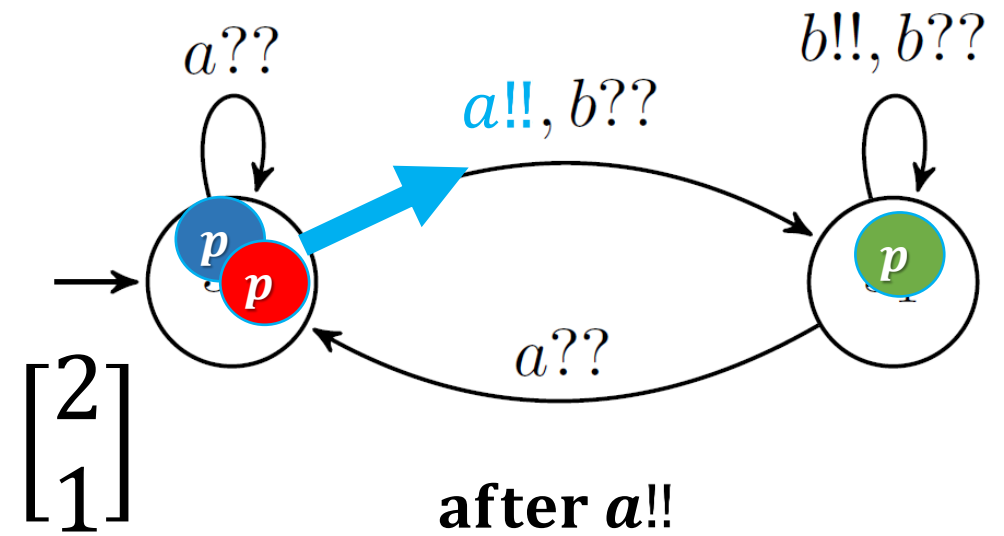
one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

A simple BP and its execution



state vector



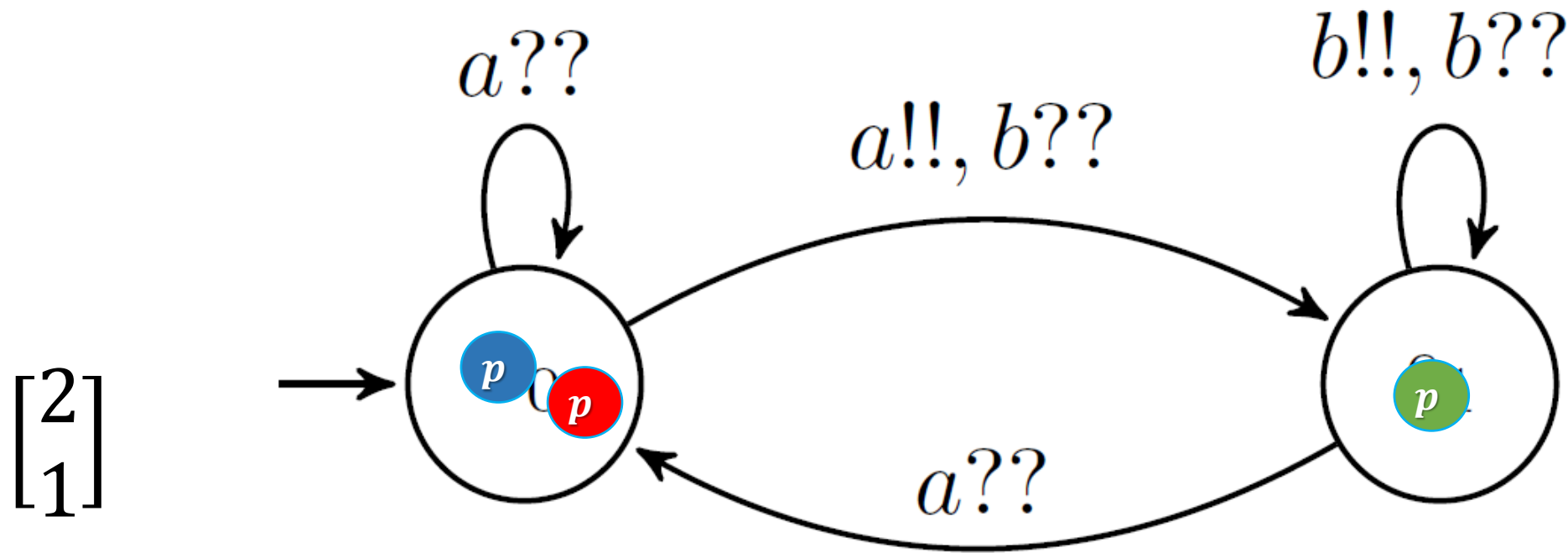
state vector

after $a!!$

one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

A simple BP and its execution



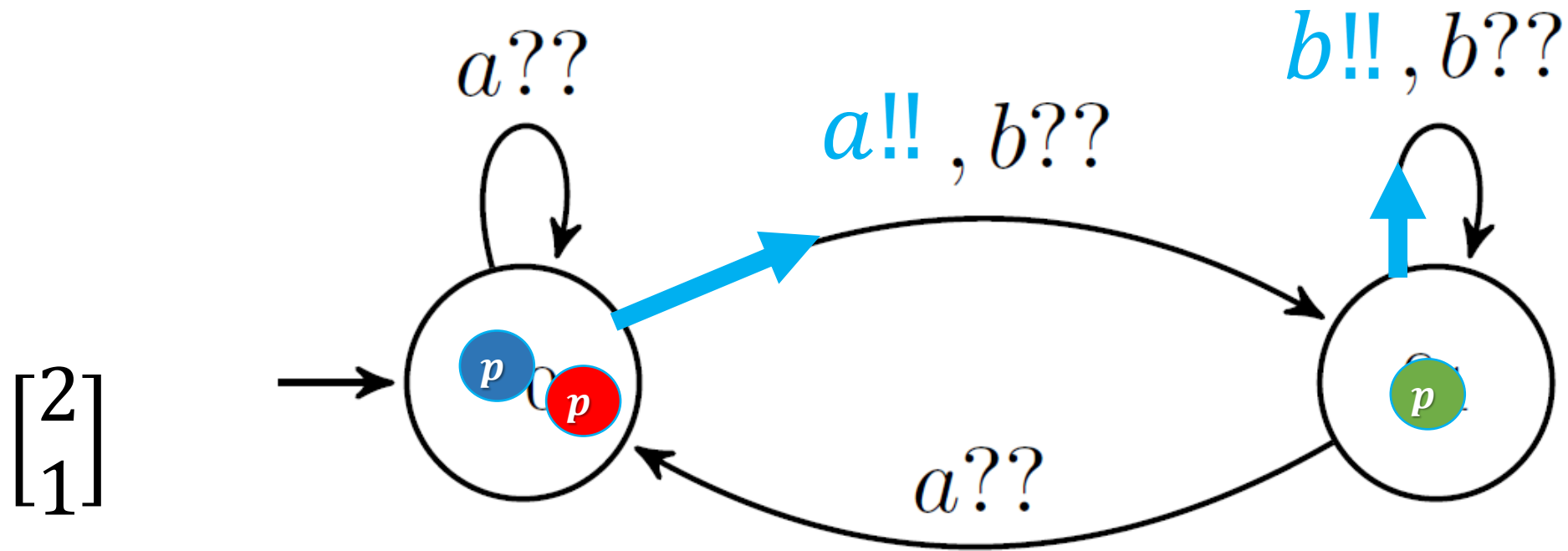
$\begin{bmatrix} 2 \\ 1 \end{bmatrix}$

state vector

one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

A simple BP and its execution



$\begin{bmatrix} 2 \\ 1 \end{bmatrix}$

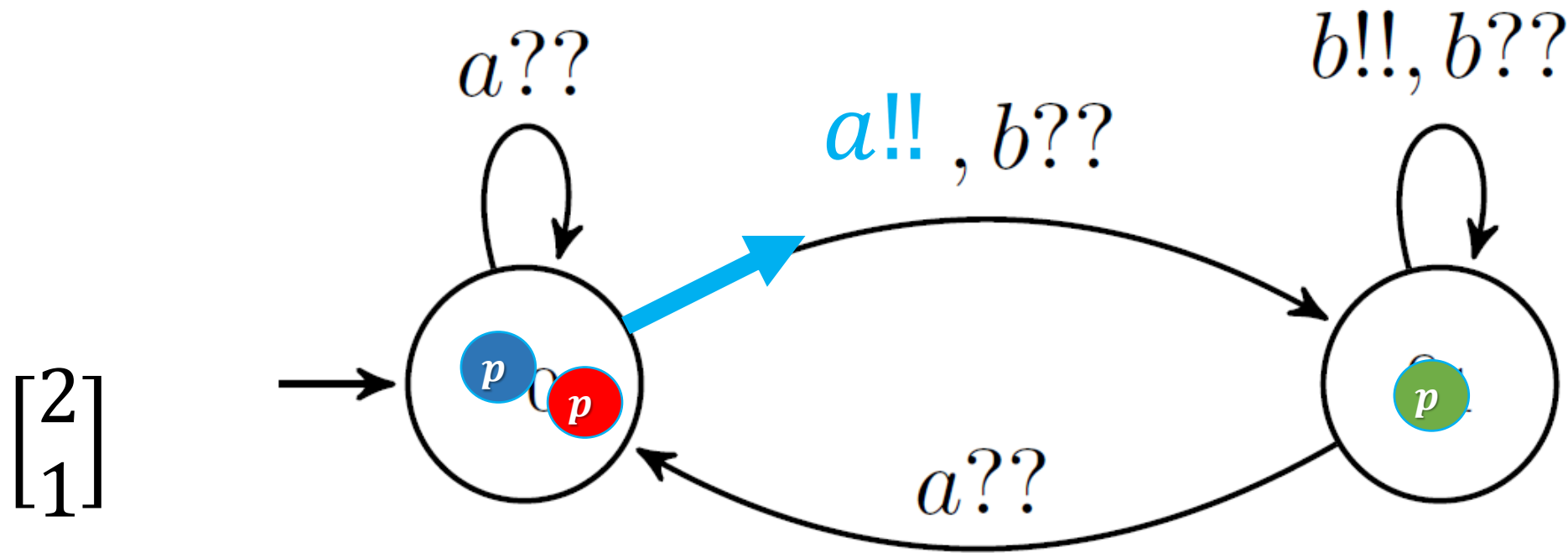
state vector

one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

A simple BP and its execution

action a is being broadcasted

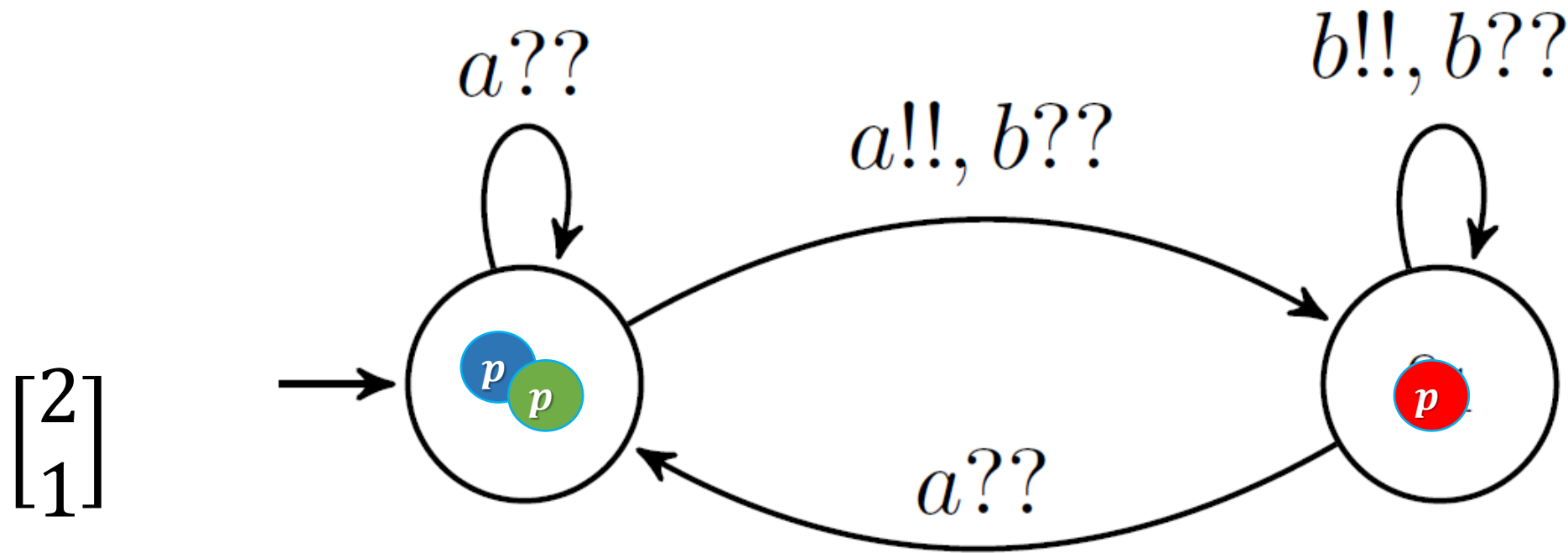


one process, the sender, takes a $\sigma!!$ transitions

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A simple BP and its execution

action a is being broadcasted

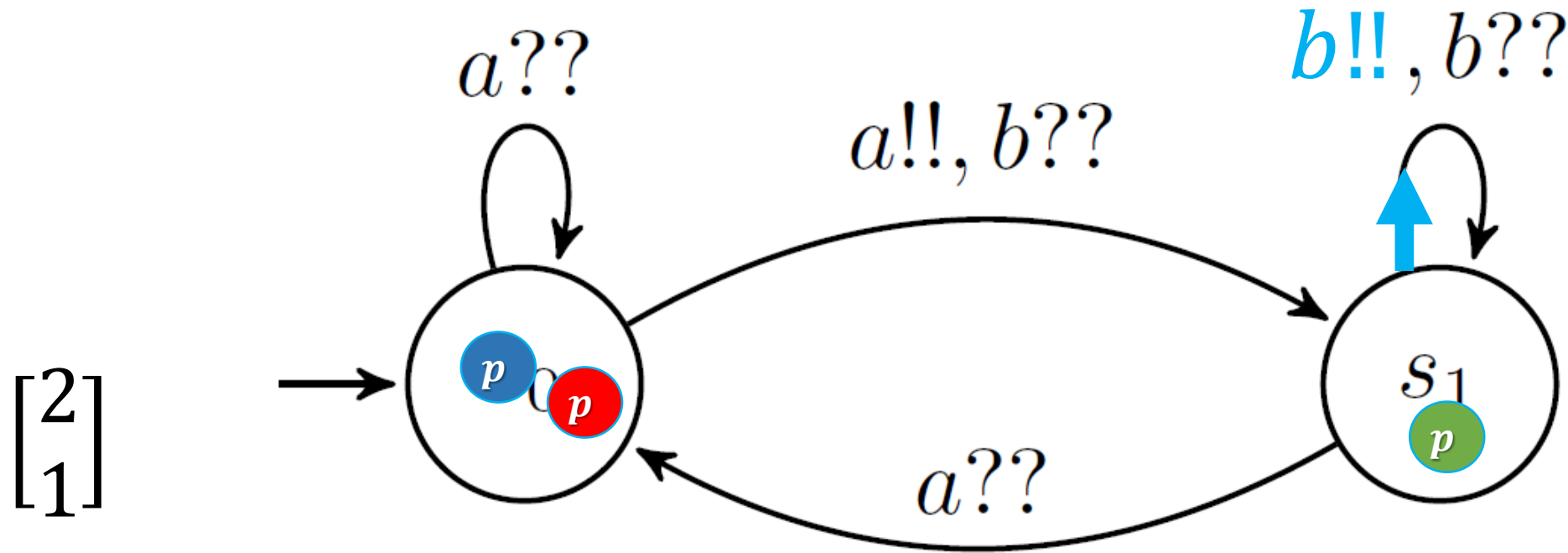


one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

A simple BP and its execution

action b is being broadcasted

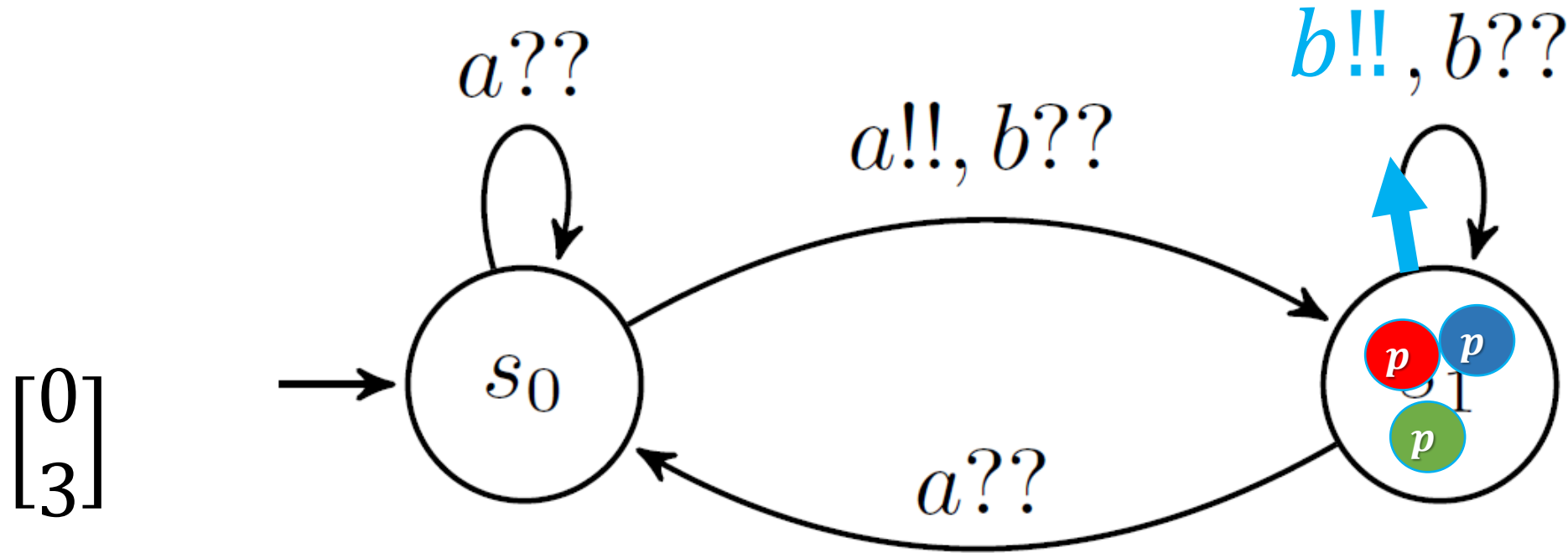


one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

A simple BP and its execution

action b is being broadcasted



$\begin{bmatrix} 0 \\ 3 \end{bmatrix}$

state vector

one process, the sender, takes a $\sigma!!$ transitions

all the other processes, the receivers, respond by following the $\sigma??$ transitions

Note that $\mathcal{L}(P^1) \subseteq \mathcal{L}(P^2) \subseteq \mathcal{L}(P^3) \subseteq \dots$

Are these inclusions strict, or does there exist an n s.t. adding more processes does not change the language?

Cutoff

If $\exists n \in \mathbb{N}$ s. t. $\forall m > n \ \mathcal{L}(P^n) = \mathcal{L}(P^m)$

If such an n exists, then the system has a **cutoff**, n .
Otherwise, we say there is no cutoff.

Fine BPs

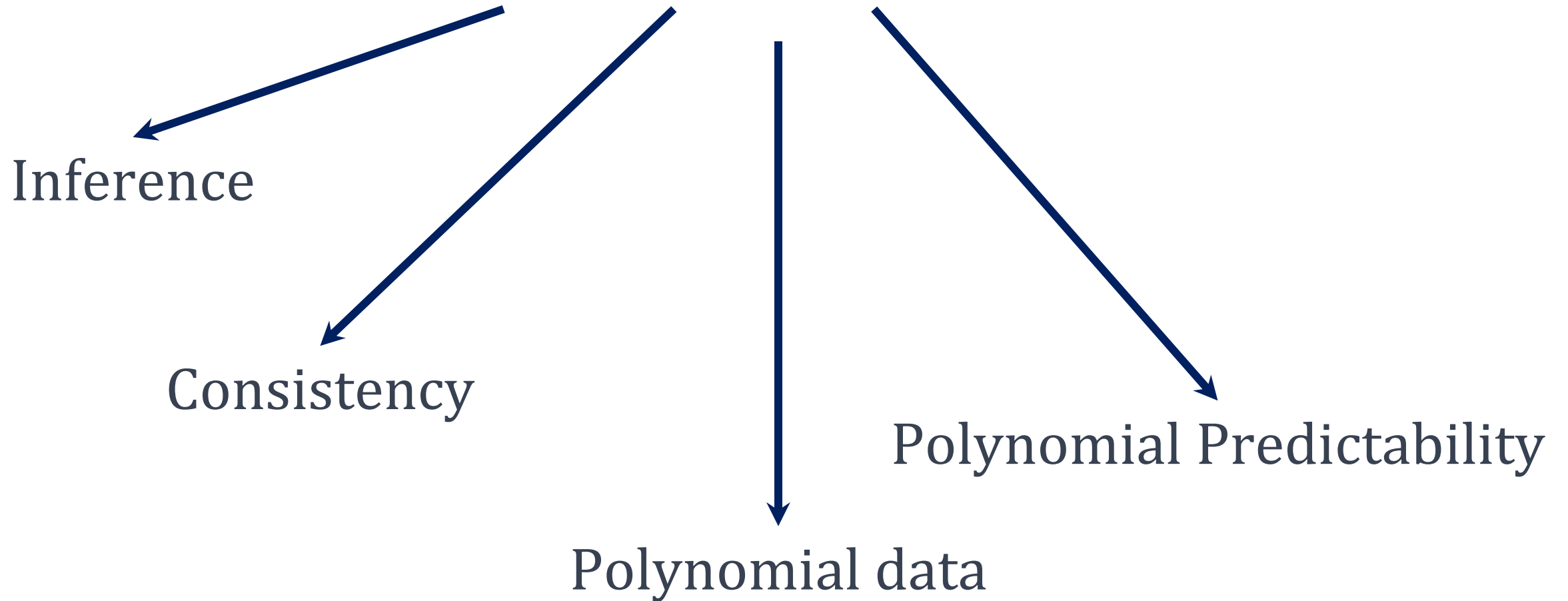
A BP that:

1. Has no **hidden** states
2. A cutoff **exists**

Learning paradigms



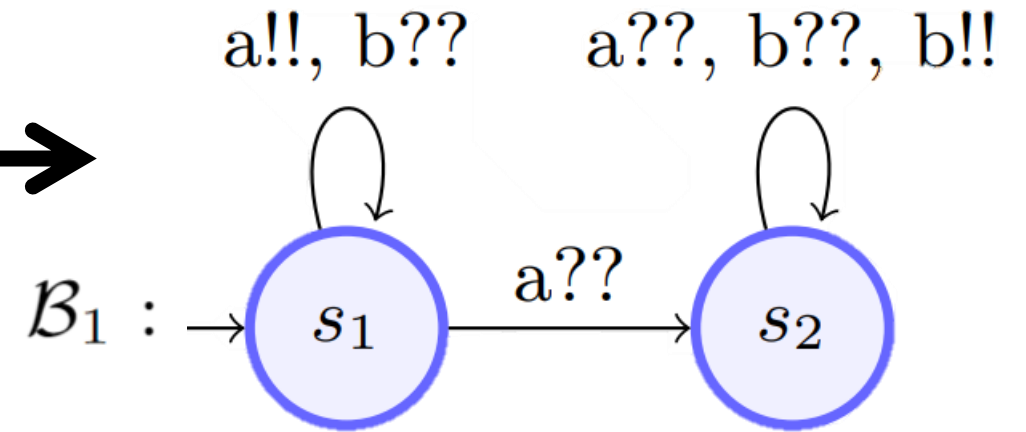
Learning paradigms



Protocols Inference

+	-
$aab, 2$	$ab, 1$
$aaa, 1$	$bba, 2$
$abbb, 6$	$b, 1$
...	...

Consistent sample

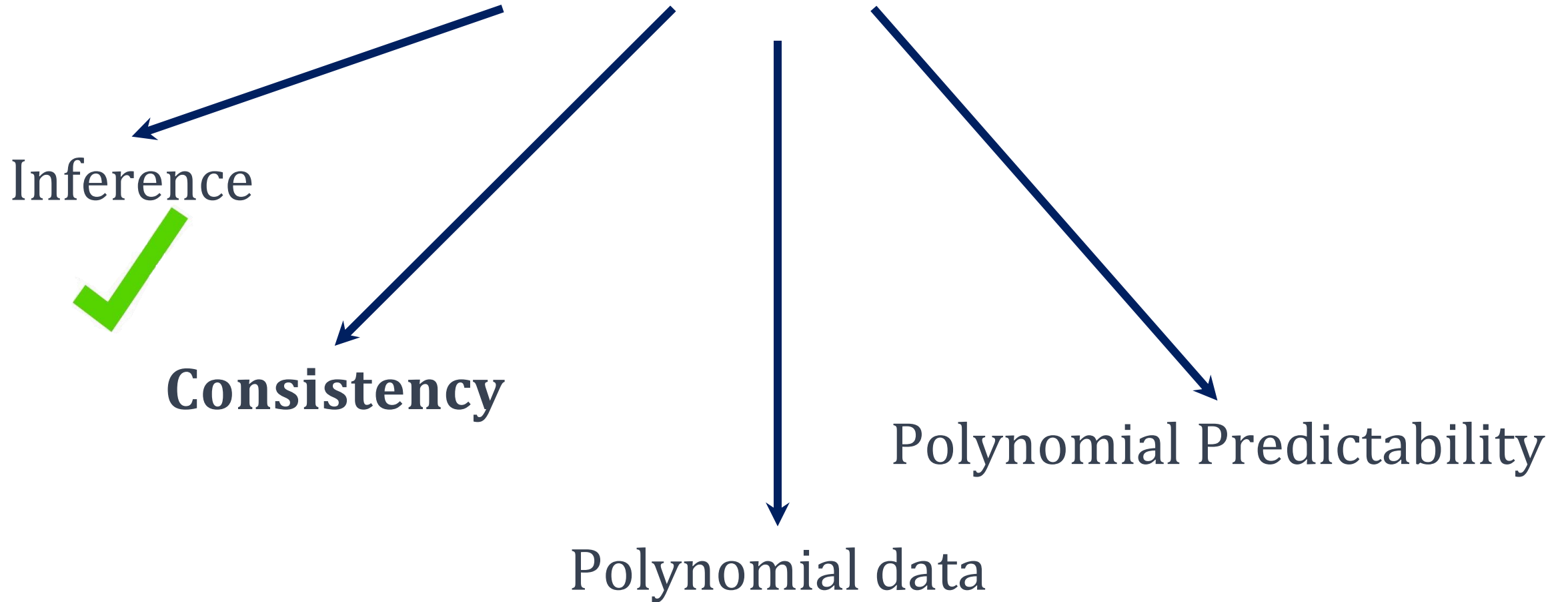


Inference

We provide an inference algorithm for BPs,
given a sample of words that are consistent with a BP,
infers a correct BP.



Learning paradigms



Consistency

Let \mathcal{C} be the class of fine BPs,

Given sample \mathcal{S} and $k \in \mathbb{N}$, determine whether there exists a BP $B \in \mathcal{C}$ consistent with \mathcal{S} with at most k states.

Consistency

We show that consistency is NP-hard for the class of fine BPs.



NP-Hard

Consistency

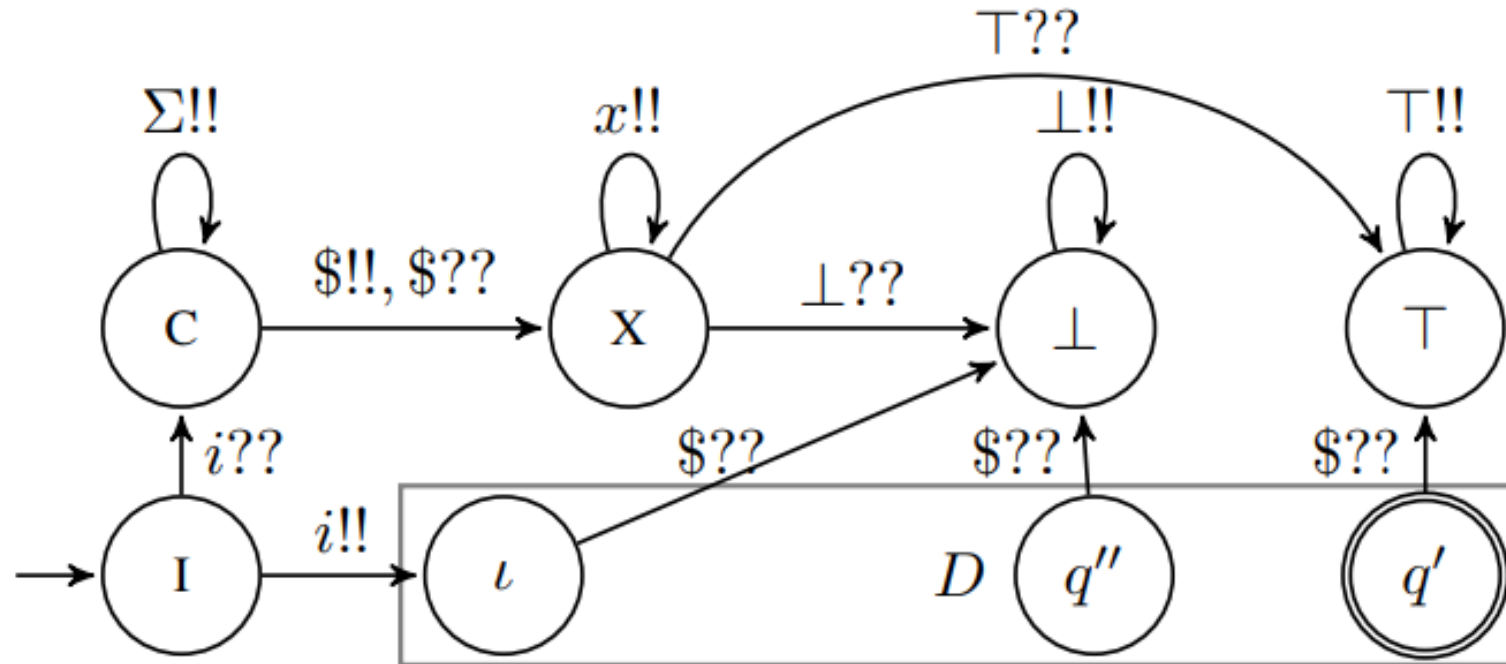
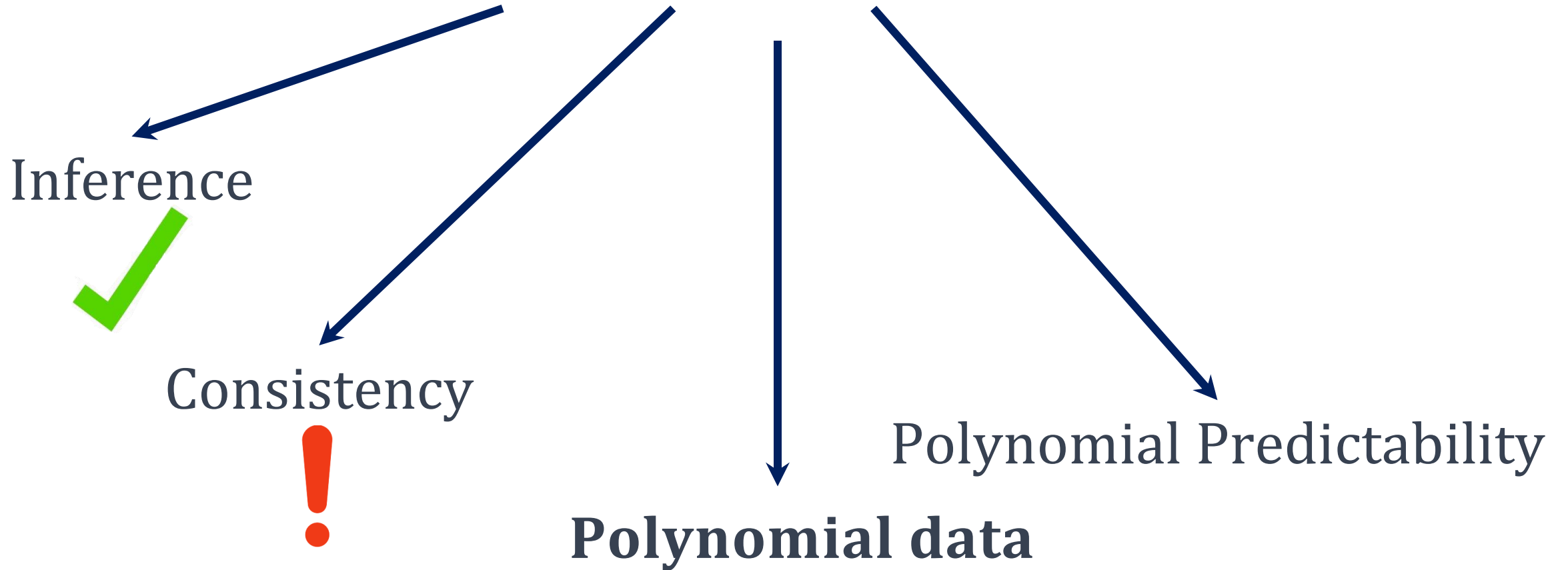


Figure 3: Reduction of DFA-consistency to BP-consistency.

Learning paradigms



Polynomial data

Is there an inference-algorithm \mathcal{A} s.t. for all BP $B \in \mathcal{C}$,
one can associate a polynomial-sized sample \mathcal{S}_B
so that \mathcal{A} correctly infers $\mathcal{L}(B)$ from any sample
subsuming \mathcal{S}_B .

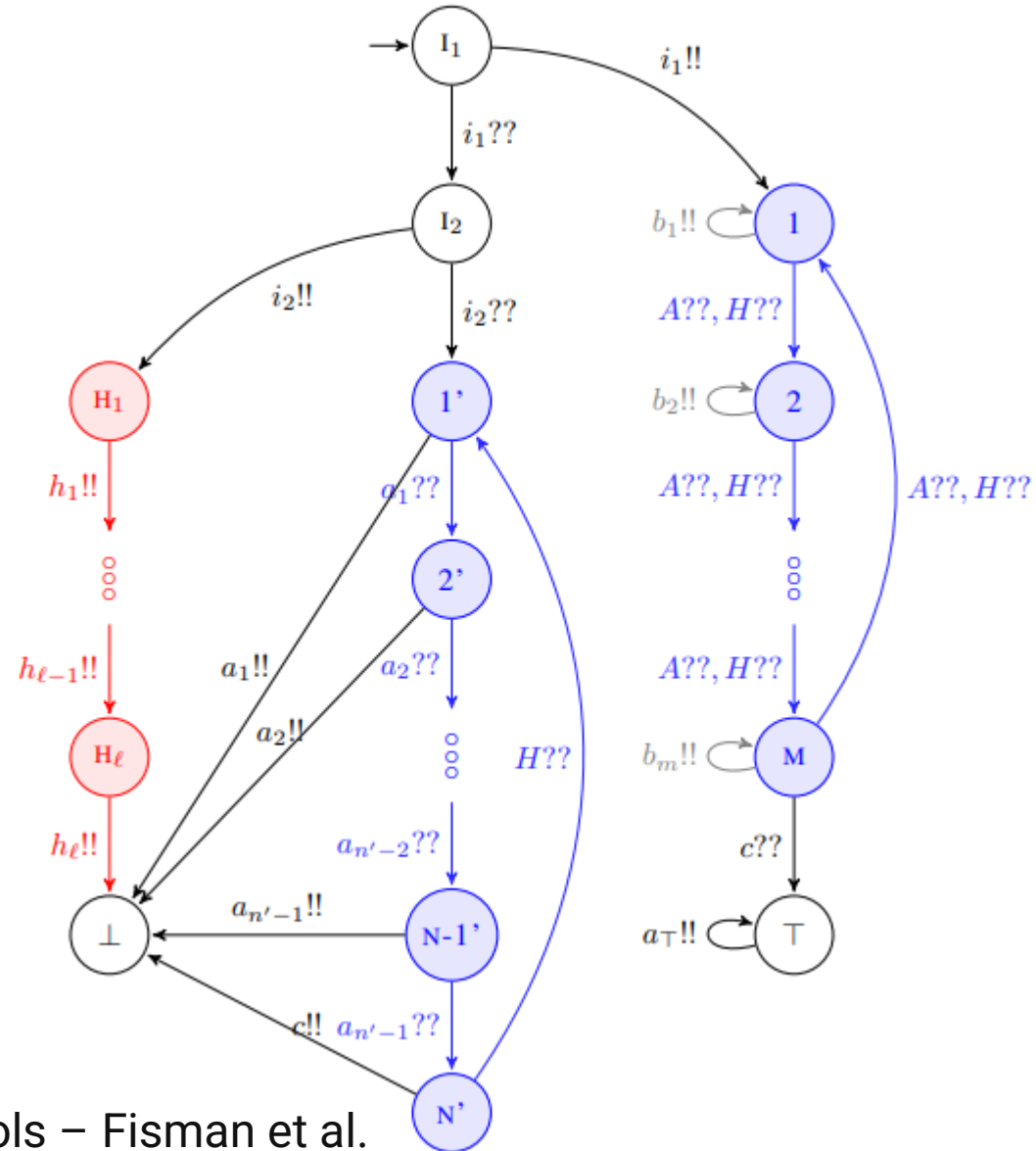
Recall: We mark the class of fine BPs as \mathcal{C} .

Polynomial data

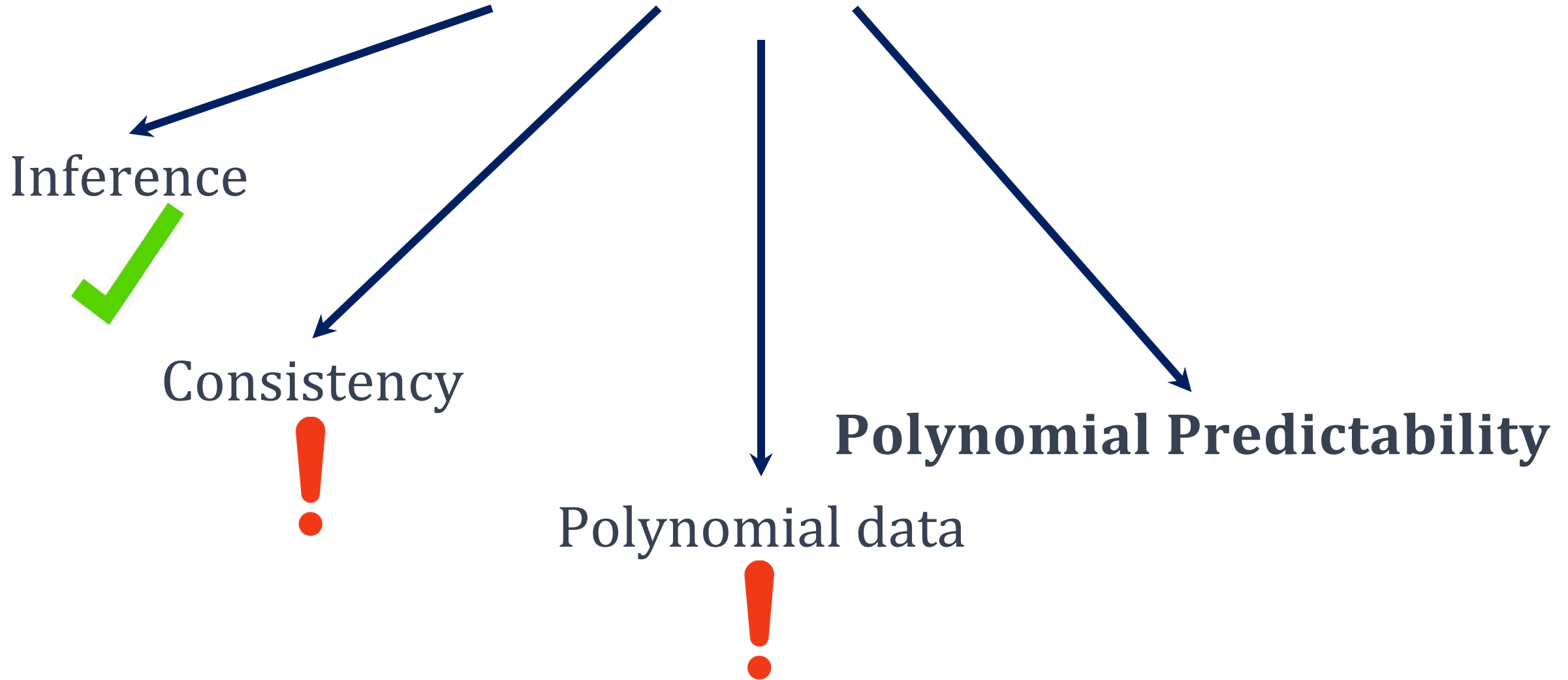
We show that there exist fine BPs
for which there is no characteristic set of polynomial size.



Polynomial data



Learning paradigms



Polynomial Predictability

Can a learner correctly classify an unknown word with high probability after asking polynomially many membership queries.

Polynomial Predictability

We show that under plausible cryptography assumptions, fine BPs (thus BPs in general) are not polynomially predictable.



Polynomial Predictability

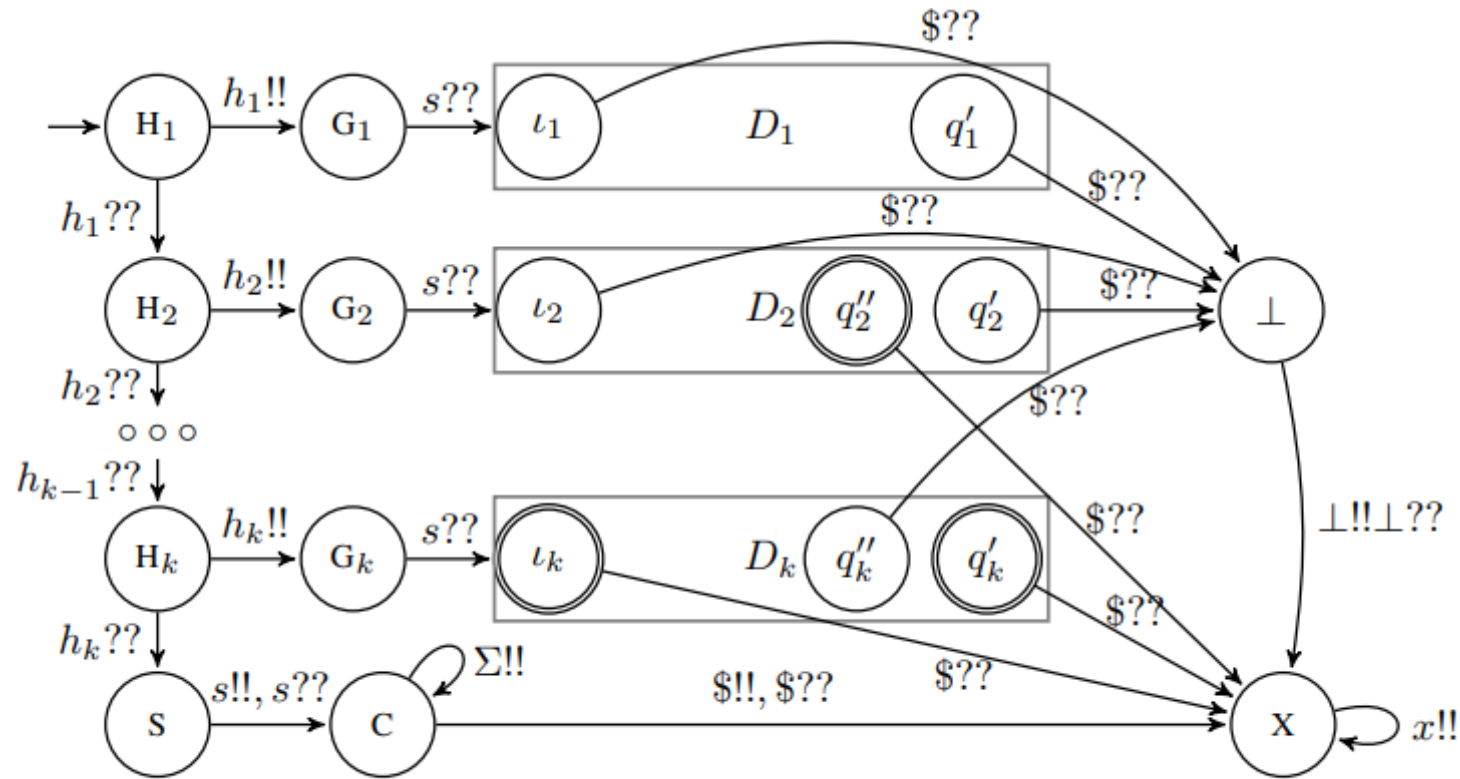


Figure 4: A BP simulating intersection of k DFAs.

Learning paradigms

