# Automated Creation of Work Distribution Functions for Parallel Best-First Search

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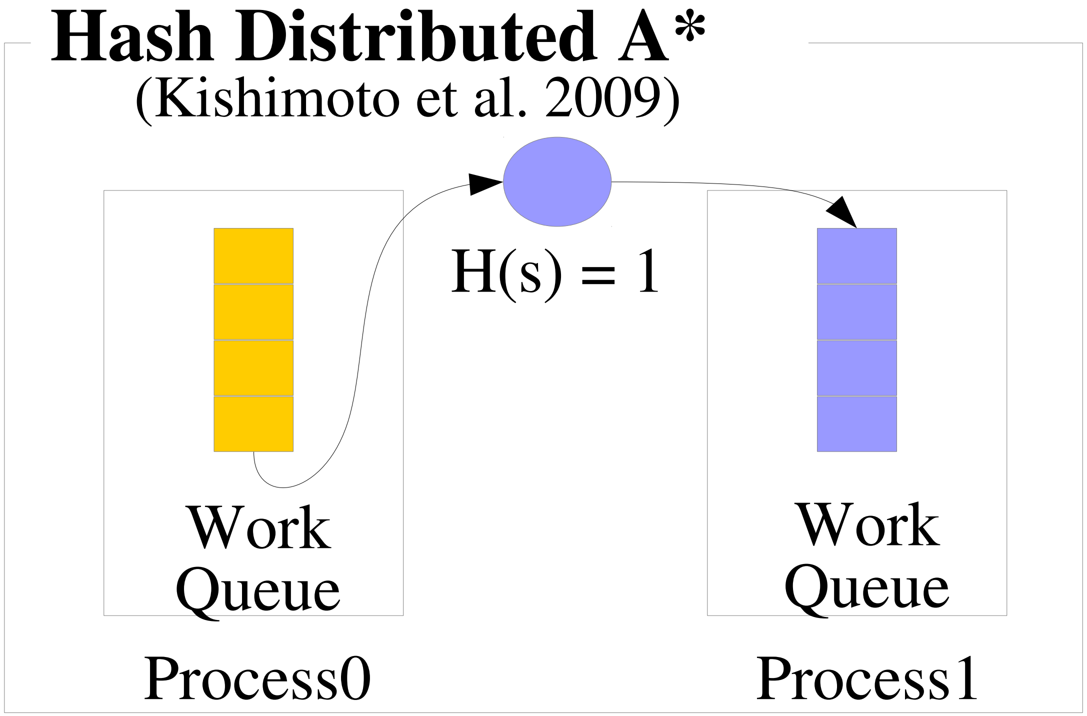
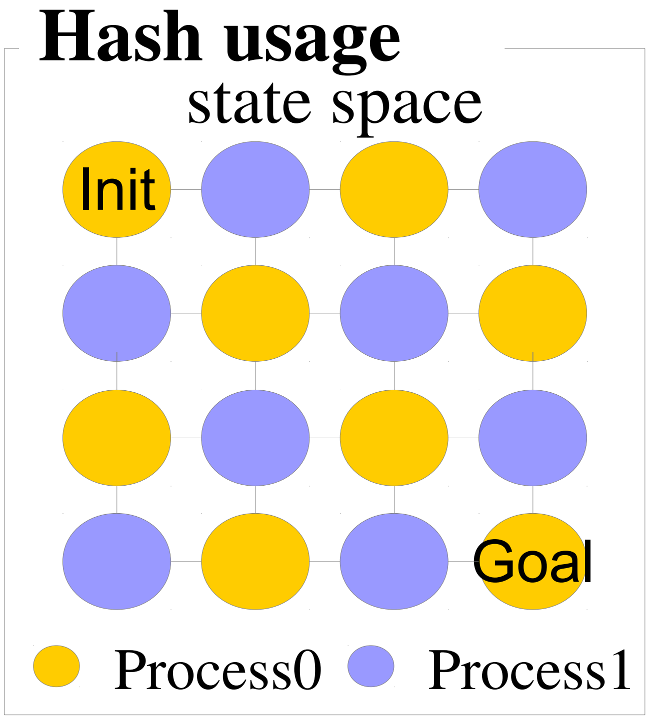
# Hash Distributed A* (HDA*)

Kishimoto, Fukunaga, & Botea (2009)

Hash Distributed A* (HDA*) is parallel A* which distributes nodes according to a hash function which assigns each state to a unique process.




As HDA* relies on the hash function for load balancing, **the choice of hash function is significant to its performance!**

# Overview of Talk

**Zobrist hashing (ZHDA*)**
(Zobrist 1970; Kishimoto et al. 2013)

+ good load balance
- high communication overhead

**State abstraction (AHDA*)**
(Burns et al. 2010)

- worse load balance
+ low communication overhead

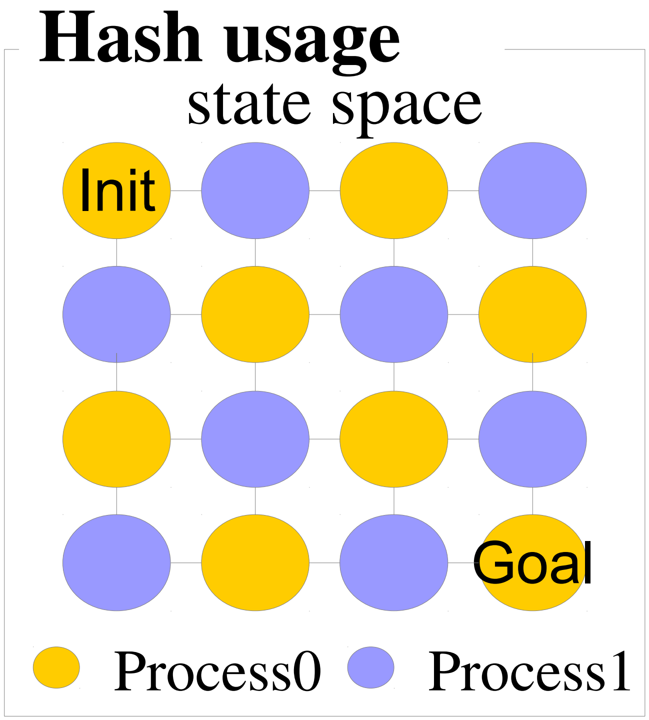
**Abstract Zobrist Hashing (AZHDA*)**
(Jinnai&Fukunaga 2016)

+ good load balance
+ low communication overhead
* requires **feature abstraction** as a parameter

**This presentation proposes a method to automatically generate efficient feature abstraction for Abstract Zobrist hashing**

# Hash Function for HDA*

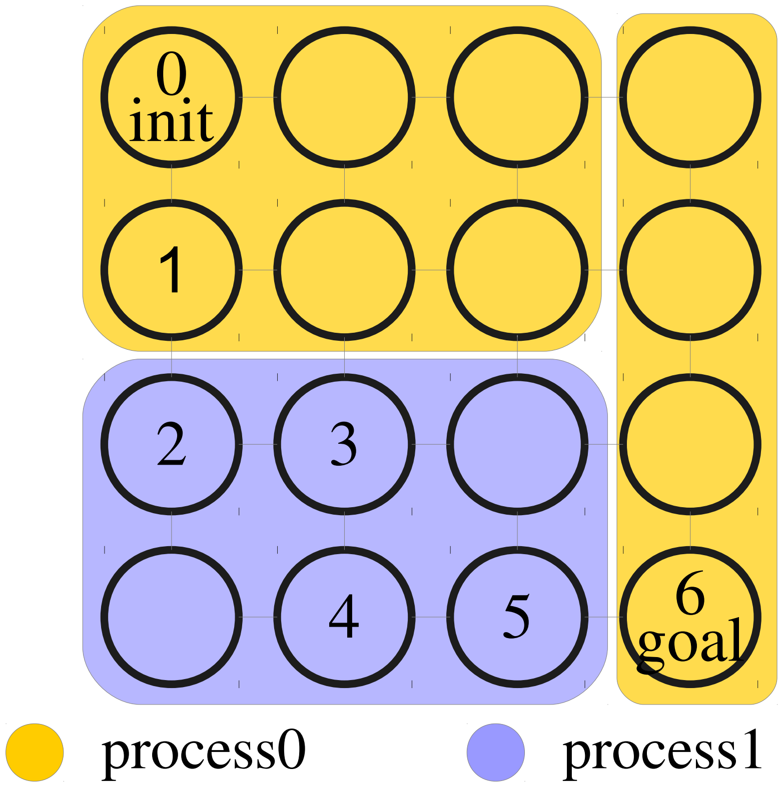
- State ($s$) is given as a set of features $x_i$:
  state $s$ = ($x_1$, $x_2$,...,$x_n$)
- Given a state $s$, a hash function $H(s)$ returns the process which owns the state $s$



# Hash Function for HDA*

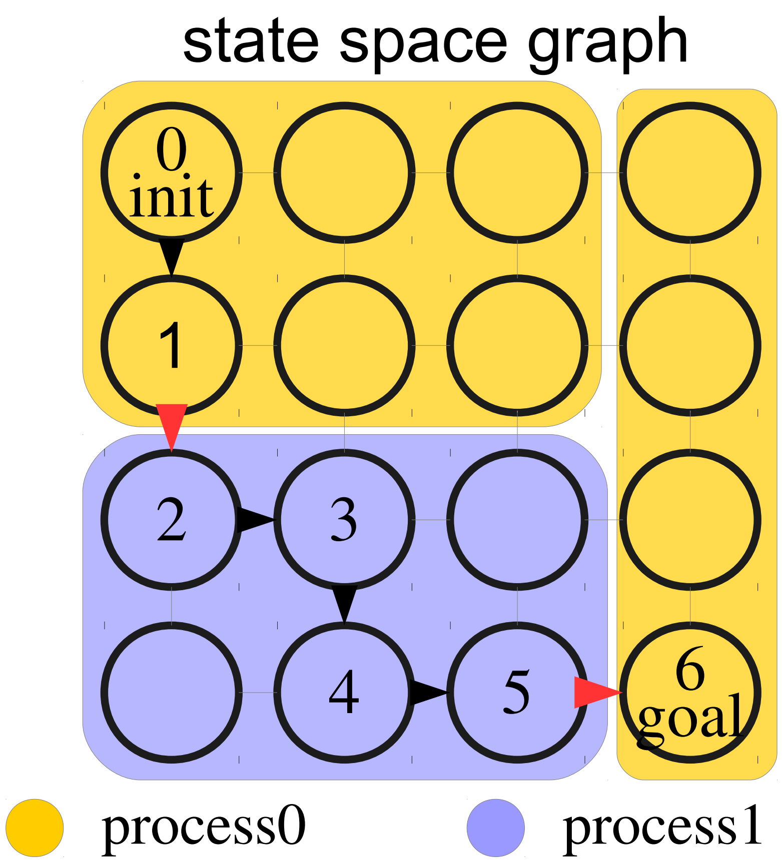
- We want $H(s)$ to be balanced
  $\rightarrow$ load balance

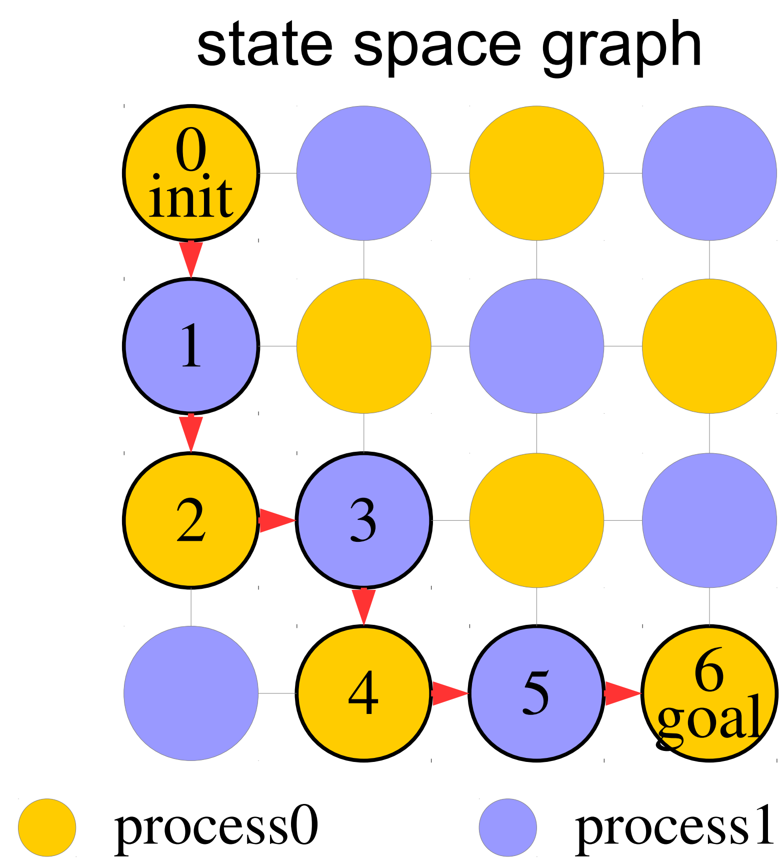
state space graph



# Hash Function for HDA*

- We want $H(s)$ to be balanced
  $\rightarrow$ load balance
- We want the value of $H(s)$ to not change frequently
  $\rightarrow$ communication overhead



# Zobrist Hashing (ZHDA*)

Zobrist (1970); Kishimoto et al. (2009)

- Goal: Distribute nodes uniformly among processes
- Method: Initialize a table of random bit strings $R$, $XOR$ the hash value $R_i[x_i]$ for each feature

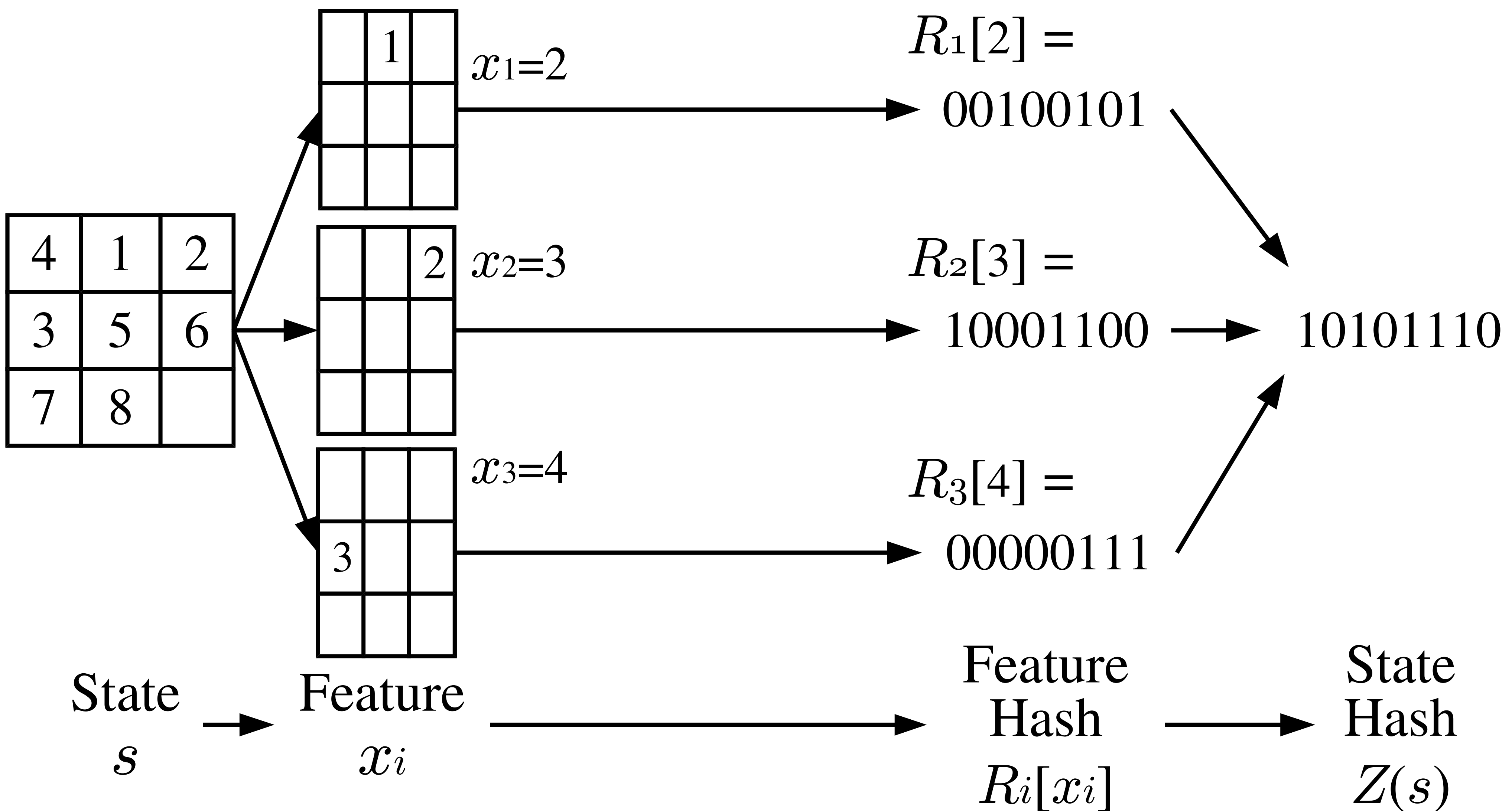
$$Z(s) = R_1[x_1] \text{ xor } R_2[x_2] \text{ xor } \ldots \text{ xor } R_n[x_n]$$

# Zobrist Hashing (ZHDA*)

Zobrist (1970); Kishimoto et al. (2009)

$Z(s)$ = $R_1[x_1]$ xor $R_2[x_2]$ xor ... xor $R_n[x_n]$

($x_i$ represents the position of tile i)

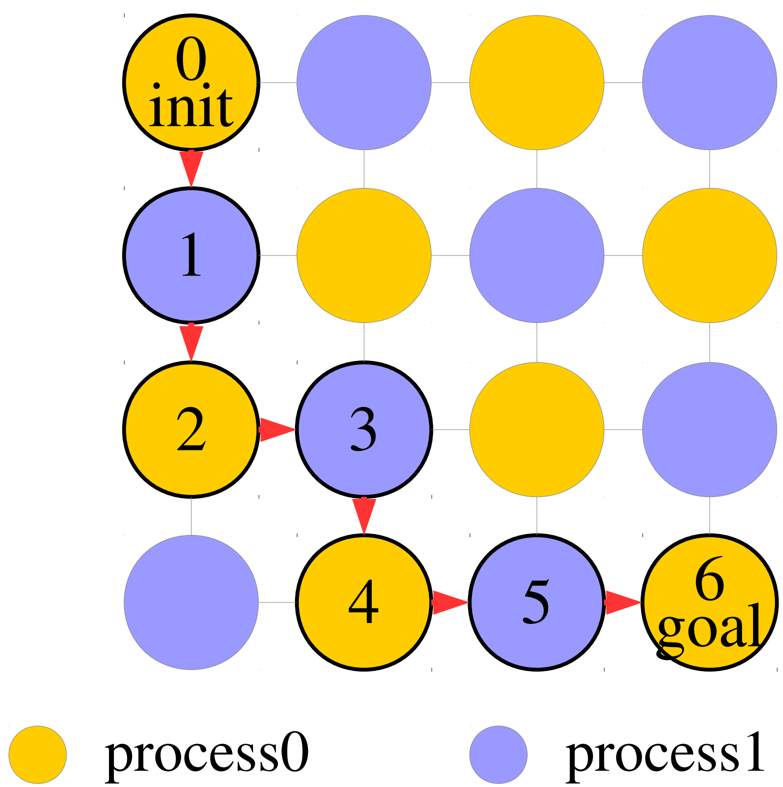


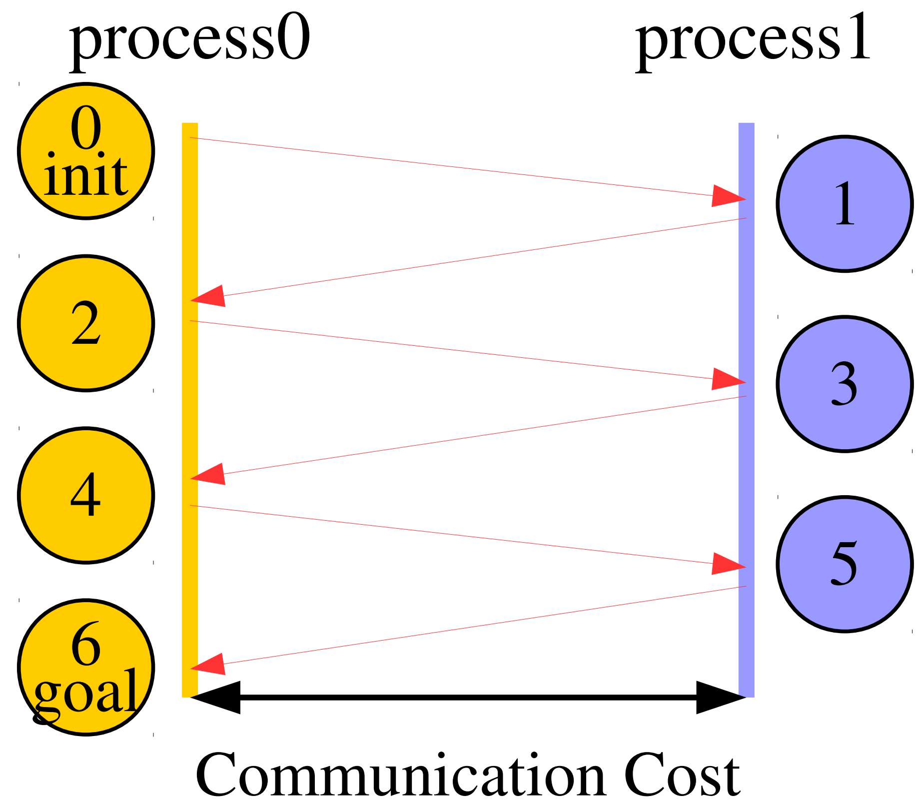
# Zobrist Hashing (ZHDA*)

Zobrist (1970); Kishimoto et al. (2009)

- Strenght: good load balance
- Limitation: high communication overhead

state space graph



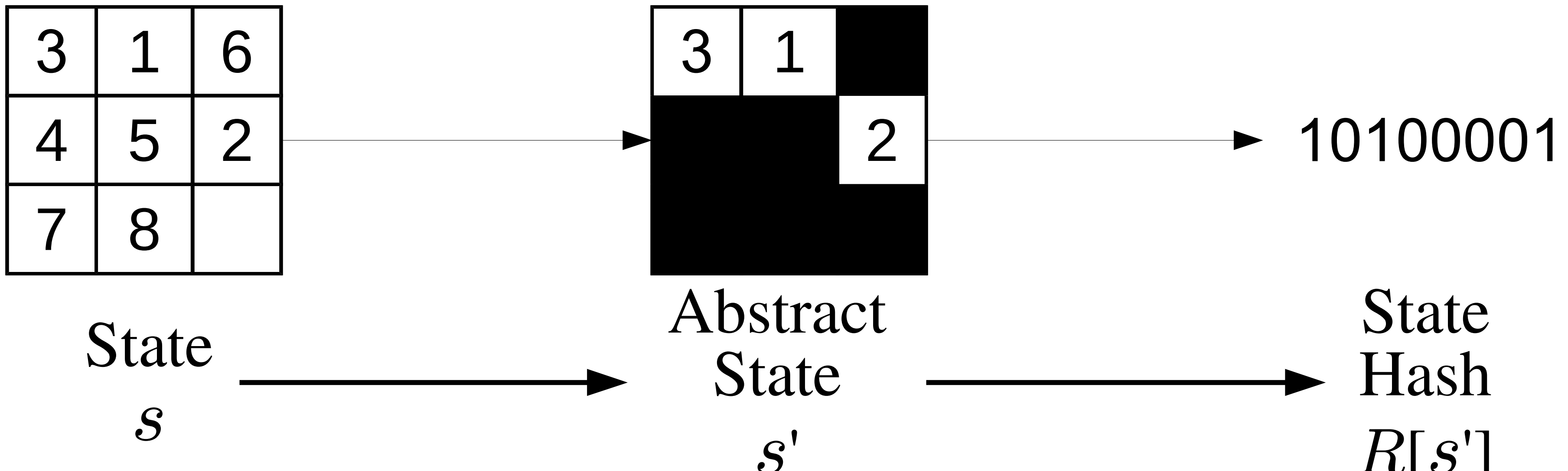
# State abstraction (AHDA*)

Burns et al. (2010)

- Goal: Assign neighbor nodes to the same process
- Method: Project states into abstract states, and abstract states are assigned to processors

$$A(s) = R[s']$$

Example: $s'$ only considers the position of tile 1,2, and 3:



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- Strenght: low communication overhead
- Limitation: worse load balance

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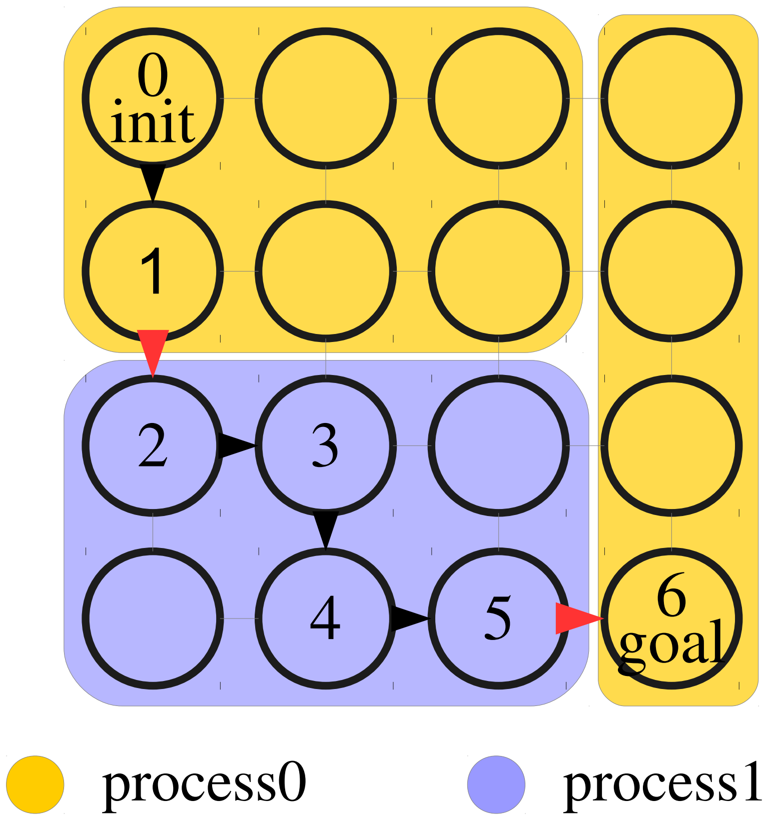


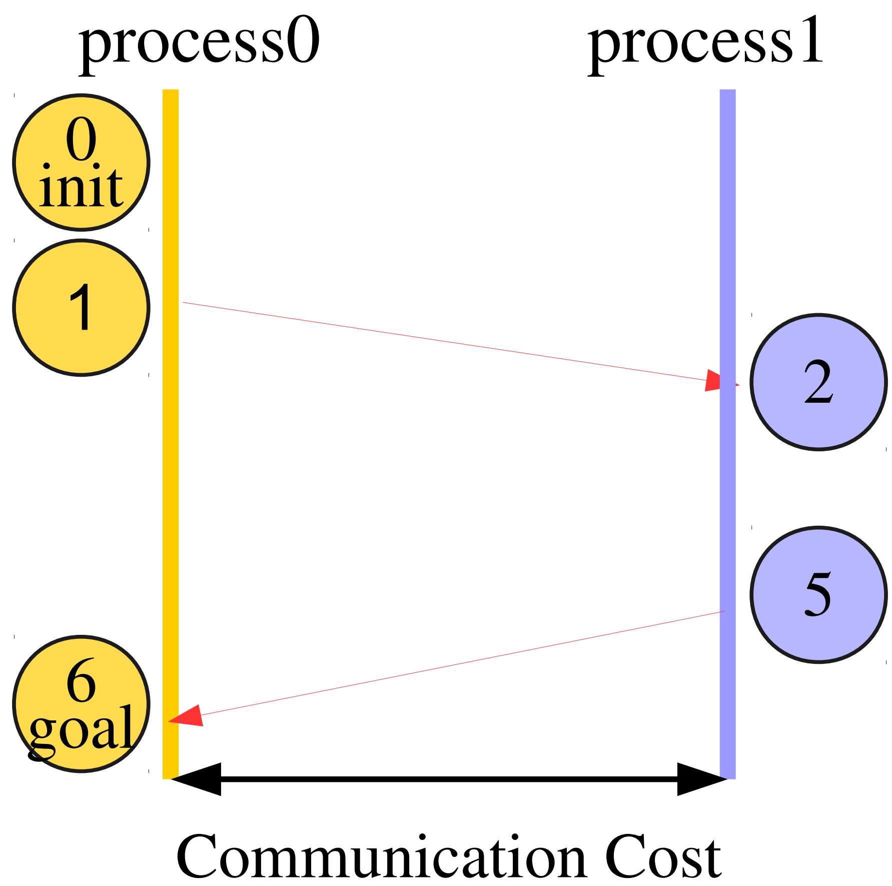

# Abstract Zobrist Hashing (AZHDA*)

Jinnai&Fukunaga (2016)

Goal: Distributes nodes uniformly while assigning neighbor nodes to the same process

Method: Apply **feature abstraction** $A_i(x_i)$ to project features into abstract features and *XOR* the hash value of each abstract feature

$$AZ(s) = R_1[A_1(x_1)] \text{ xor } R_2[A_2(x_2)] \text{ xor } \ldots \text{ xor } R_n[A_n(x_n)]$$

or

$$AZ(s) = Z(s'), \text{ where } s' = (A_1(x_1), A_2(x_2), \ldots, A_n(x_n))$$

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Jinnai&Fukunaga (2016)

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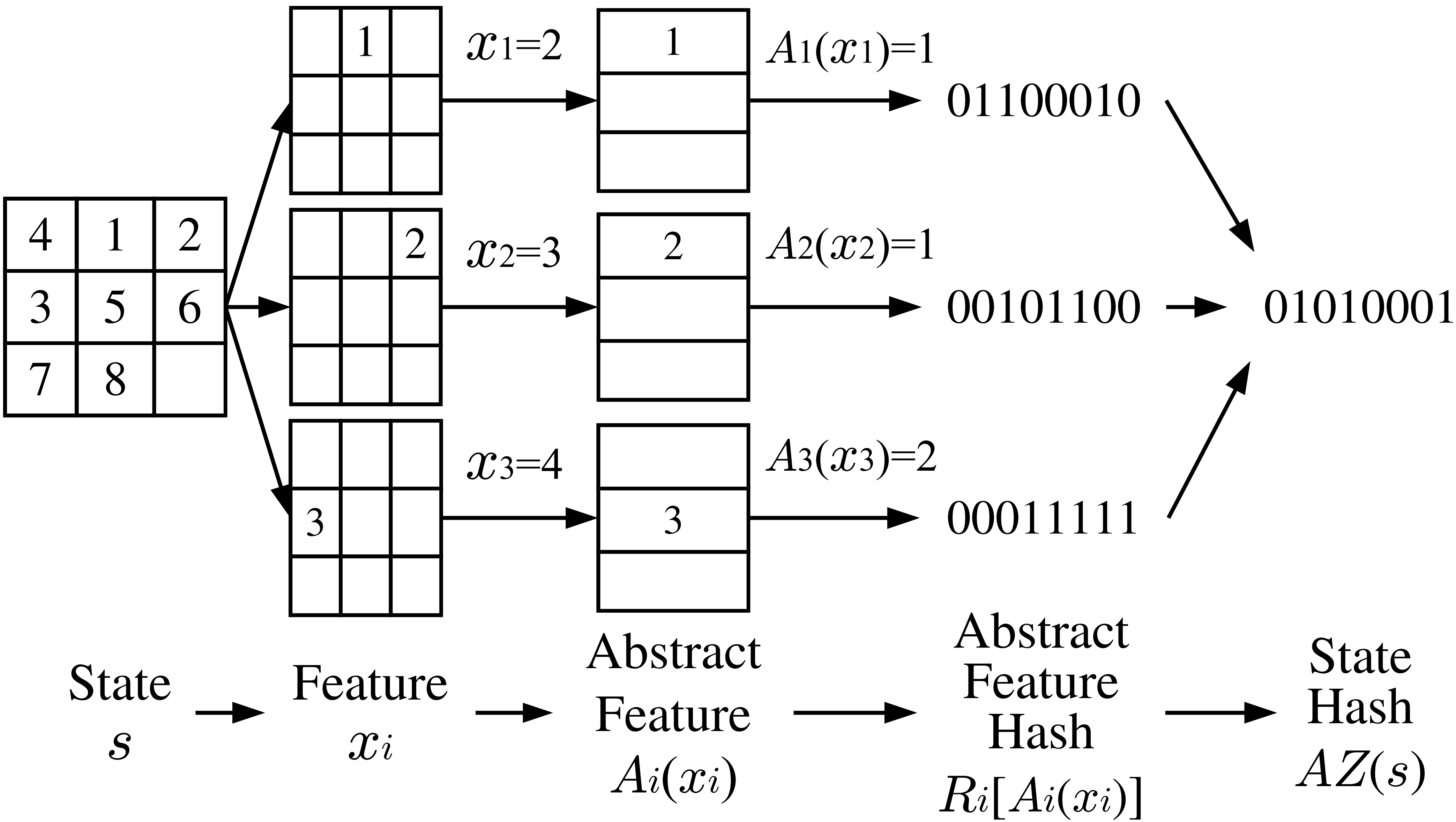

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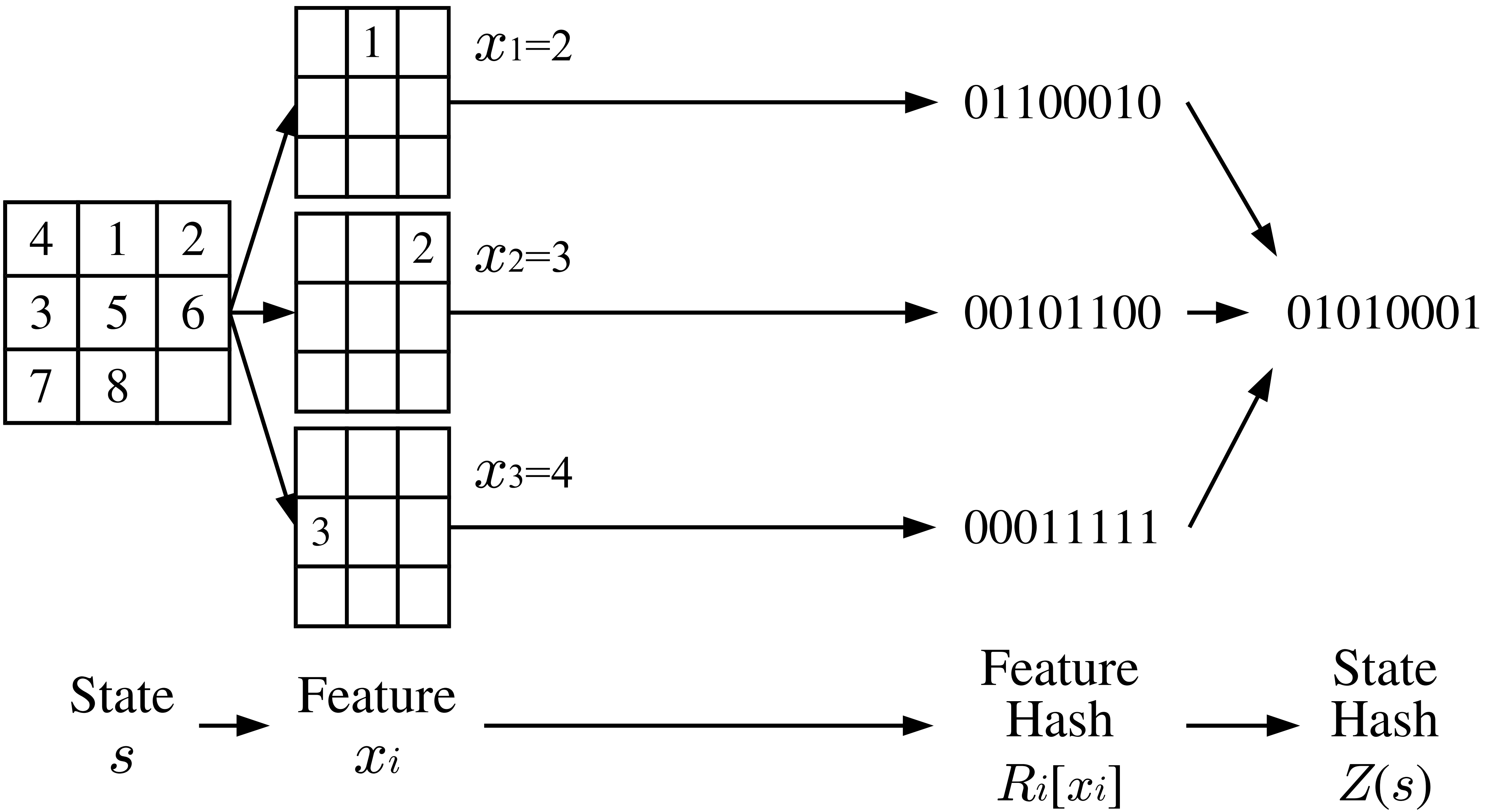

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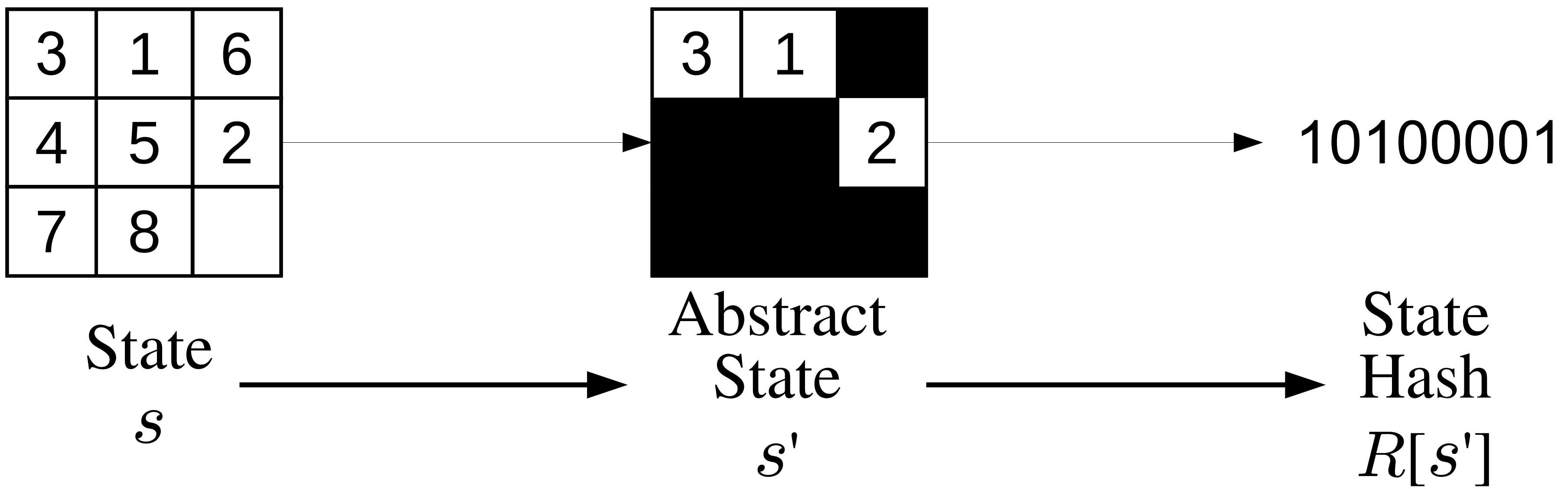

# Abstract Zobrist Hashing (AZHDA*)

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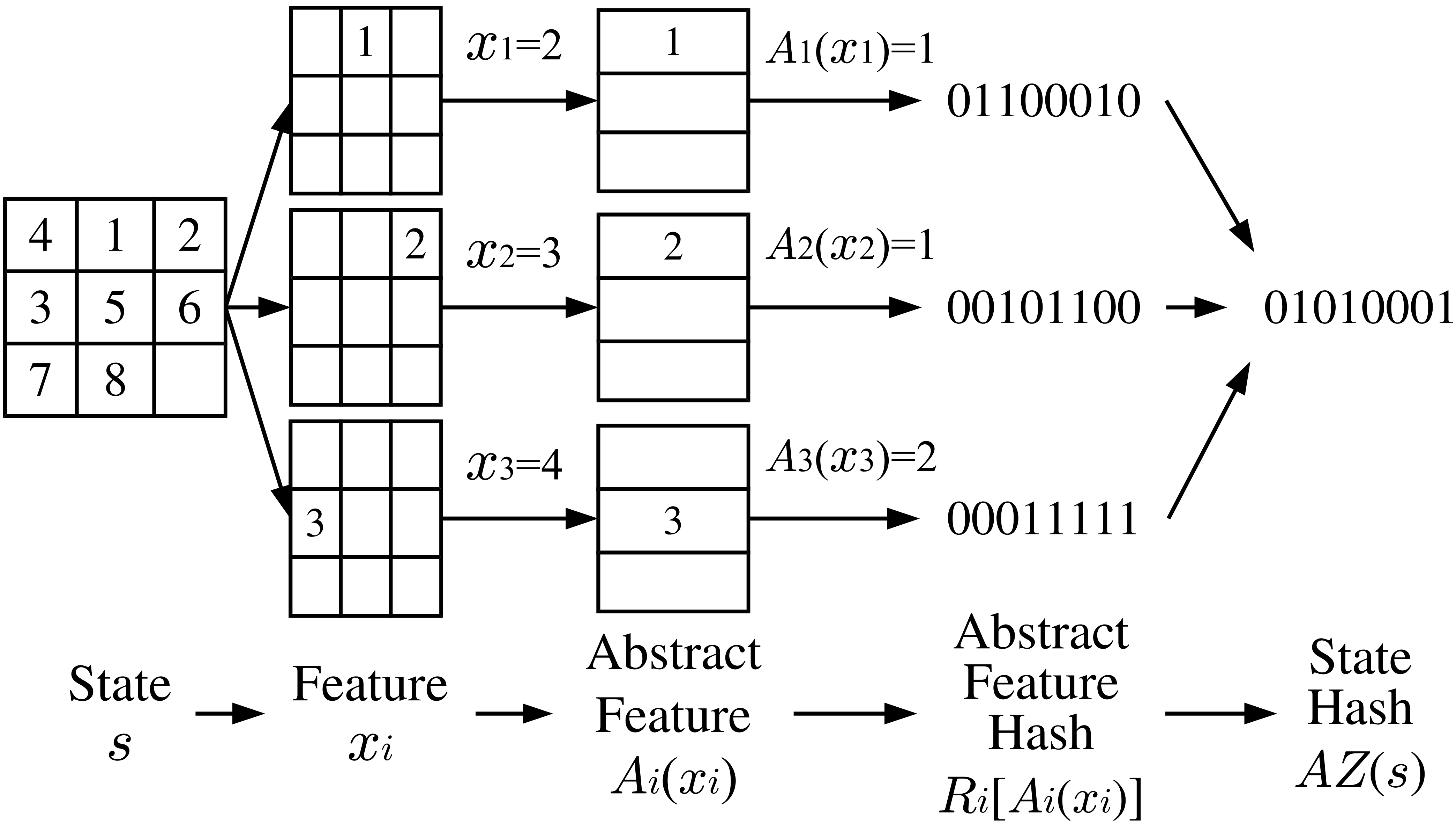
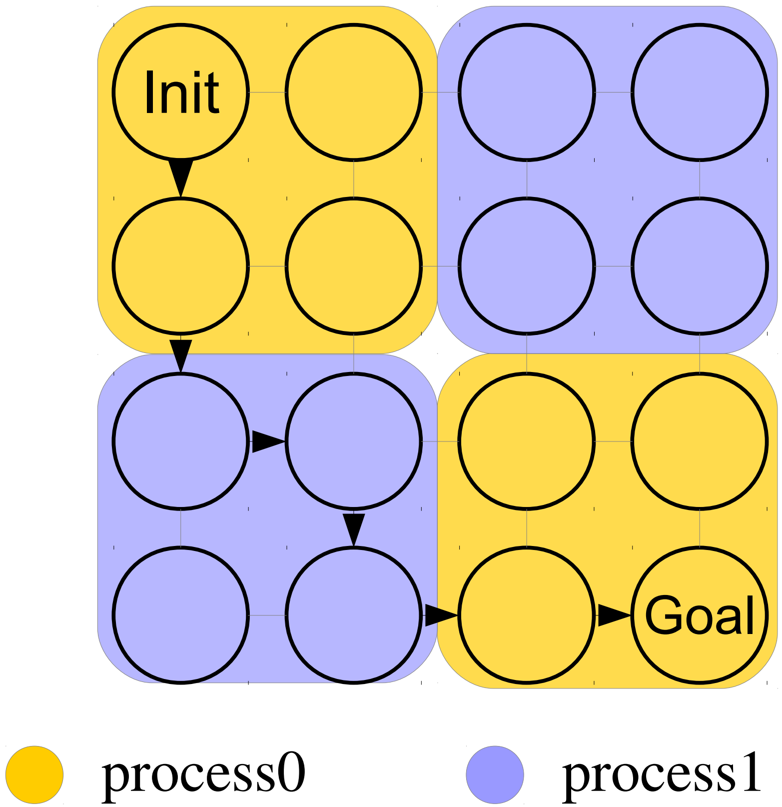


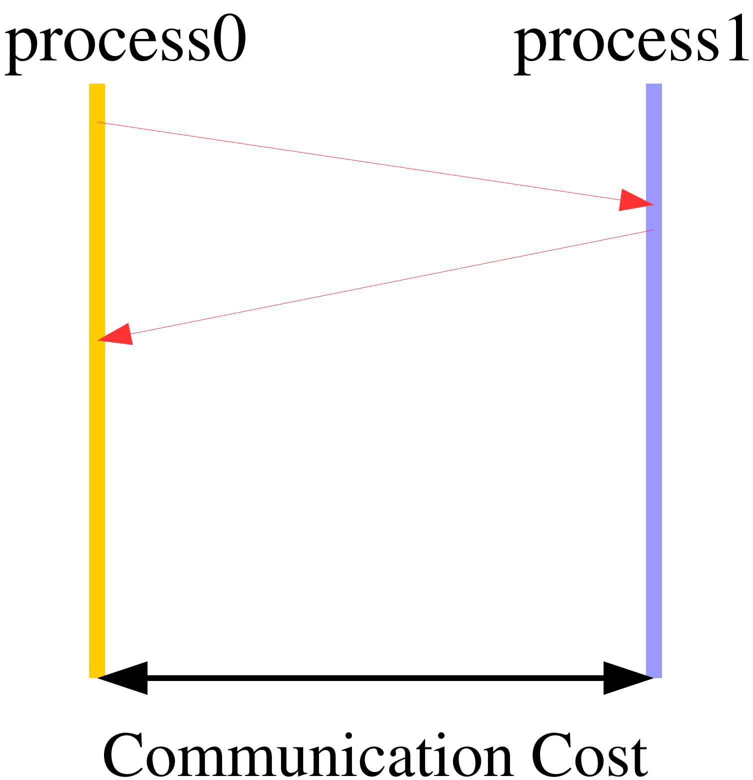
# Abstract Zobrist Hashing (AZHDA*)

Jinnai&Fukunaga (2016)

- Achieves good load balancing using Zobrist hashing
- Reduces communication overhead using feature abstraction

state space graph



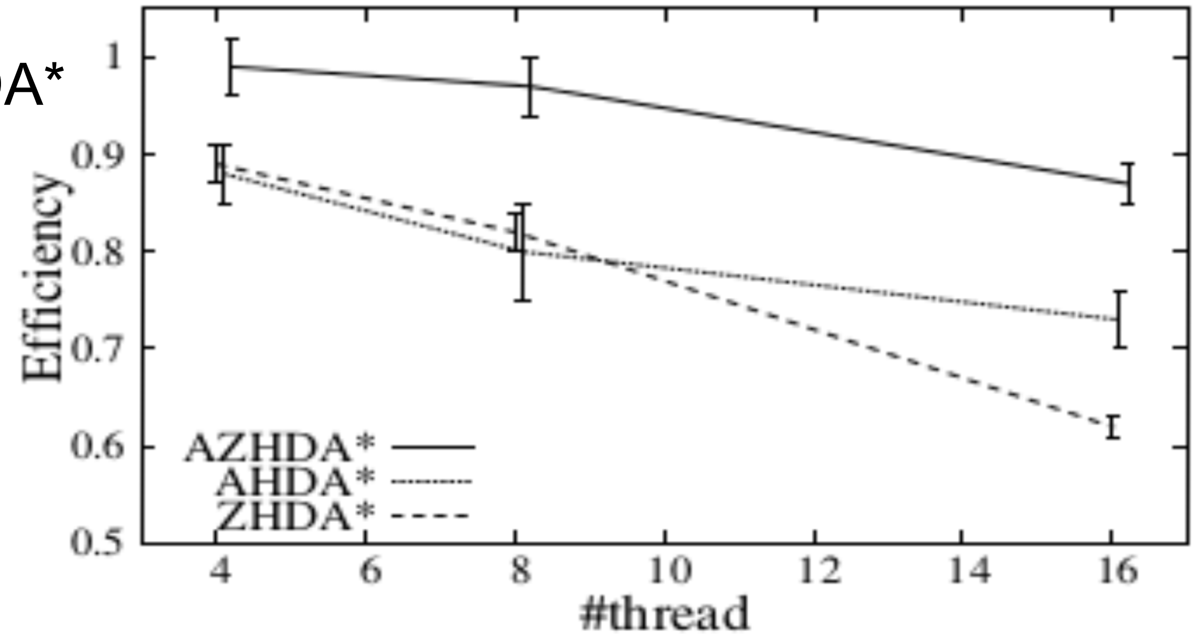
# The performance of AZHDA* with hand-crafted abstract feature

- (Jinnai&Fukunaga, 2016) showed that Abstract Zobrist hashing <u>using hand-crafted feature abstraction</u> significantly outperformed previous methods (Zobrist hashing and Abstraction)

AZHDA*:
Abstract Zobrist hashing + HDA*

AHDA:
State abstraction + HDA*

ZHDA*:
Zobrist hashing + HDA*

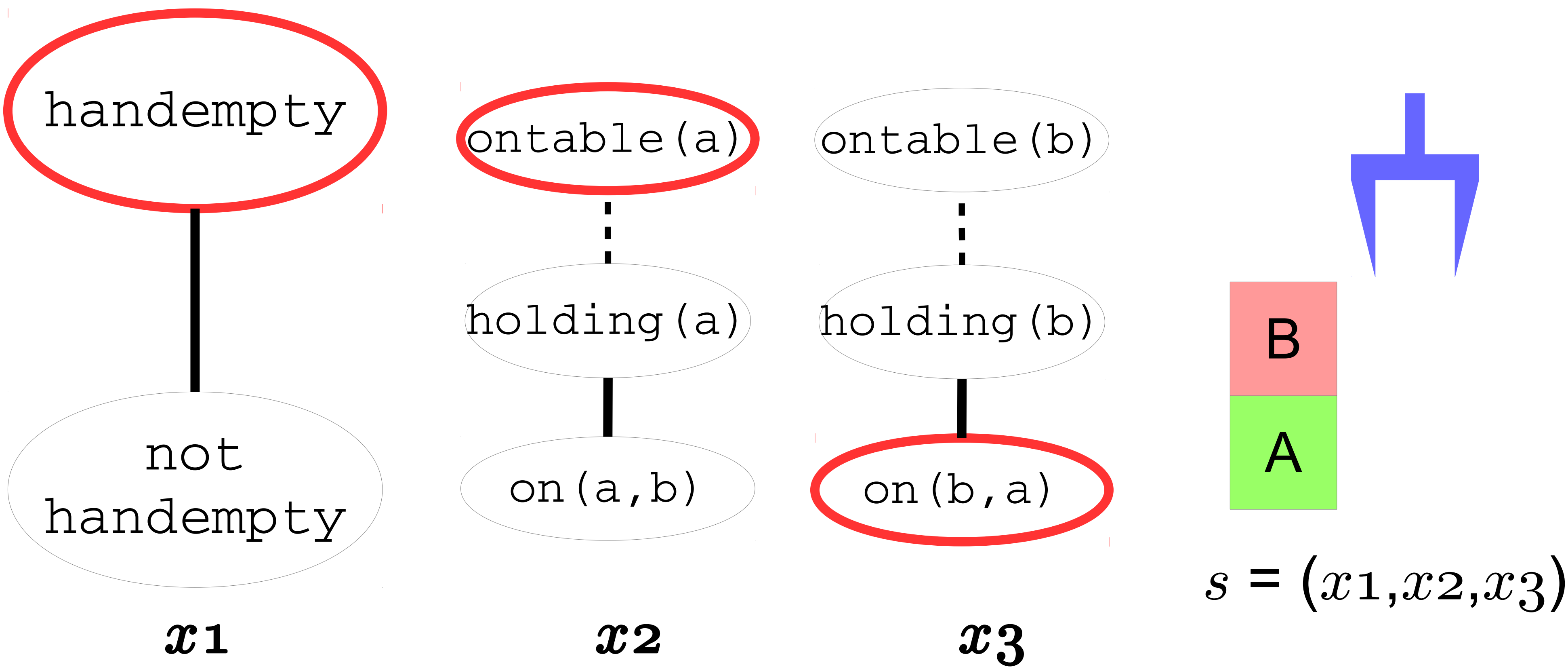



24-puzzle
(Jinnai&Fukunaga 2016)

# Zobrist hashing for planning

We can use SAS+ variables for Zobrist hashing

$$Z(s) = R_1[x_1] \text{ xor } R_2[x_2] \text{ xor } \ldots \text{ xor } R_n[x_n]$$

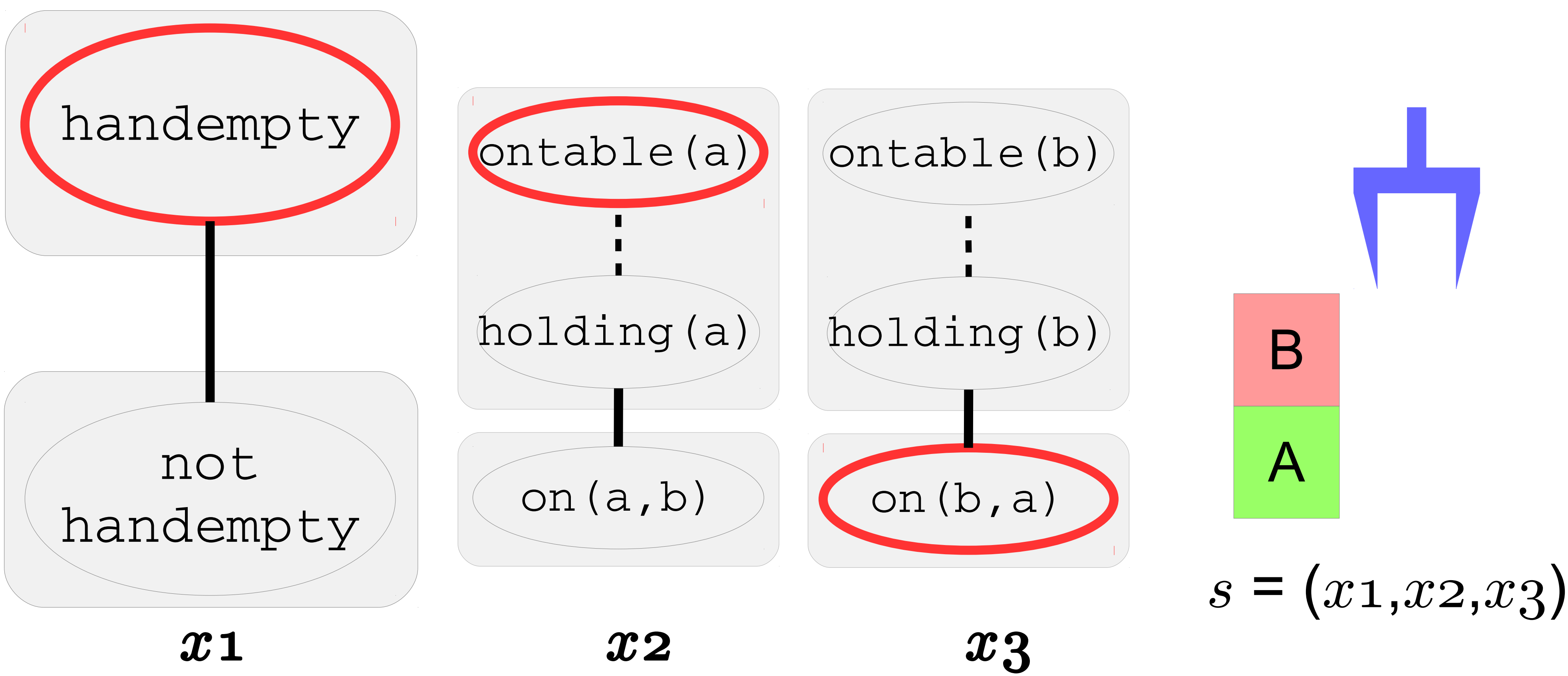



Example: blocks world

# Abstract Zobrist hashing for planning

To apply AZHDA* on domain-independent planning, we have to generate feature abstraction $A_i(x_i)$ automatically

$$AZ(s) = R_1[A_1(x_1)] \text{ xor } R_2[A_2(x_2)] \text{ xor } \ldots \text{ xor } R_n[A_n(x_n)]$$

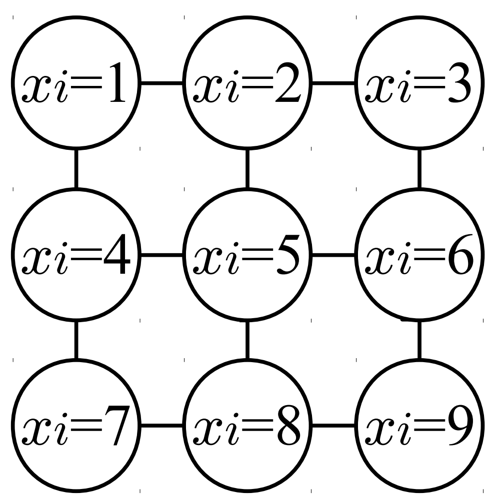



Example: blocks world

Grey squares represent feature abstraction

# Greedy abstract feature generation
(Jinnai&Fukunaga 2016)

Approach: maps each SAS+ variable $xi$ to abstract feature $S_1$ and $S_2$ based on $xi$'s domain transition graphs (nodes are values, edges are transitions)




DTG of a variable $xi$ represents the transition of the value

GreedyAFG applied to DTG of 8-puzzle

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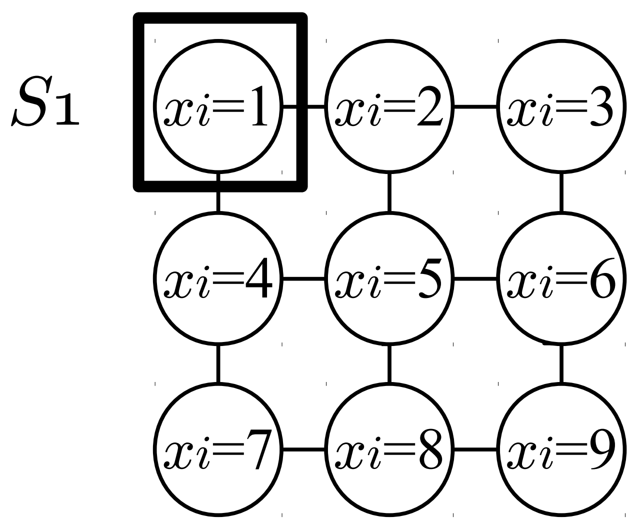


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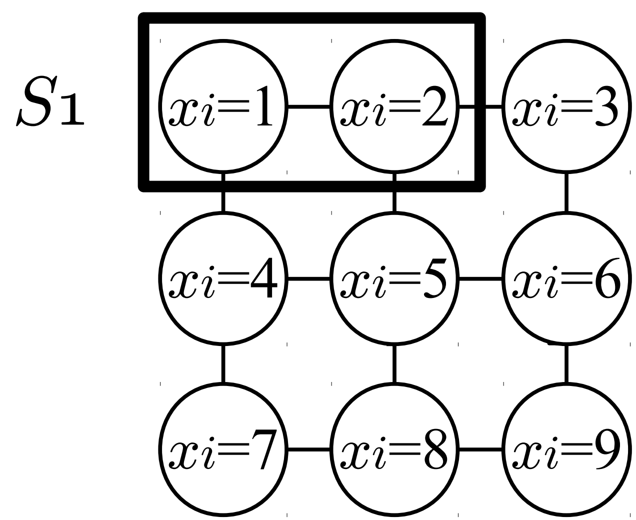
1. Assign the minimal degree node to $S_1$
2. Add to $S_1$ the unassigned node which shares the most edges with node in $S_1$

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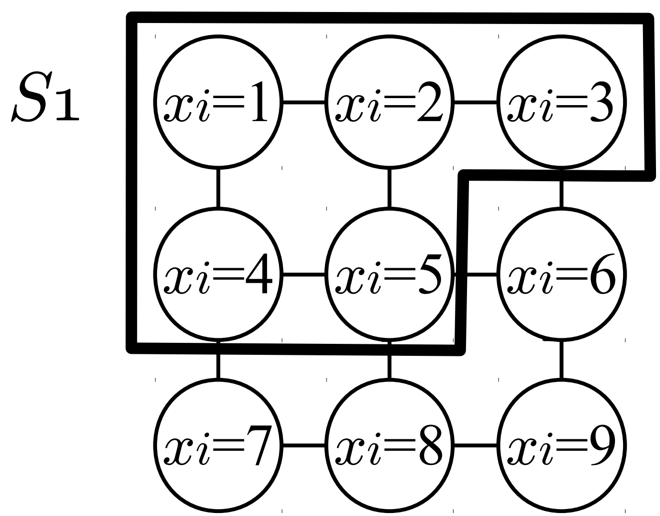
1. Assign the minimal degree node to $S_1$
2. Add to $S_1$ the unassigned node which shares the most edges with node in $S_1$
3. Until $|S_1|$ reaches the half of the DTG, repreat step 2.

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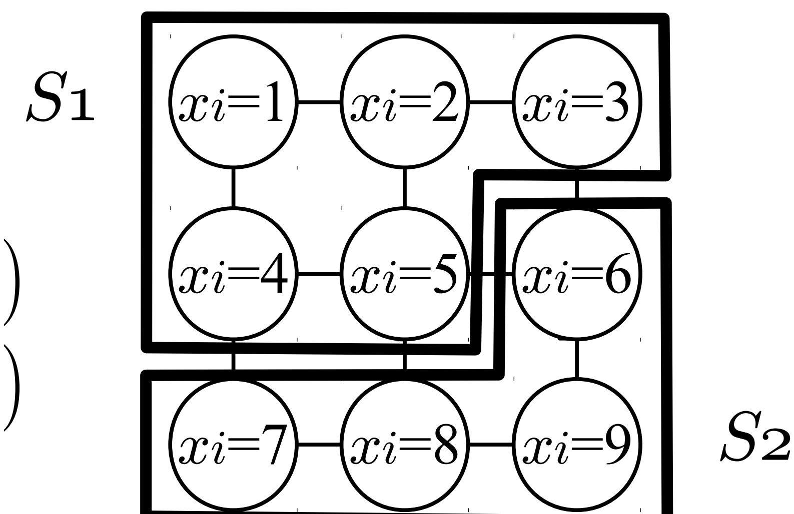
2. Add to $S_1$ the unassigned node which shares the most edges with node in $S_1$
3. Until $|S_1|$ reaches the half of the DTG, repeat step 2.
4. Assign all unassigned nodes to $S_2$

$$A_i(x_i) = \begin{cases} 1 & (if\ x_i \in S_1) \\ 2 & (if\ x_i \in S_2) \end{cases}$$




DTG of a variable $xi$ represents the transition of the value

GreedyAFG applied to DTG of 8-puzzle

# The performance of GreedyAFG
(Jinnai&Fukunaga 2016)

- Evaluated on IPC benchmarks
- Single multicore machine (8 cores)
- Pattern database heuristics
- AZHDA* using GreedyAFG achieved only a modest improvement over previous methods

| | AZH/GreedyAFG | Zobrist | Abstraction |
|---|---|---|---|
| Walltime (sec) | **282** | 298 | 341 |
| Speedup efficiency | **0.797** | 0.766 | 0.729 |
| Search overhead | 0.01 | **0.01** | 0.34 |
| Comm. overhead | 0.62 | 0.86 | **0.40** |

→ What the problem of GreedyAFG?

# Problem of GreedyAFG

- GreedyAFG incurs communication overhead if **ANY** of the abstract feature changes its value from the parent node (because a hash value is a function of a set of abstract features)

  $AZ(s)$ = $R_1[A_1(x_1)]$ xor $R_2[A_2(x_2)]$ xor ... xor $R_n[A_n(x_n)]$

- If any of the $Ai(xi)$ changes, then the value of $Ri[Ai(xi)]$ changes, then $AZ(s)$ changes (thus incurs communication overhead)

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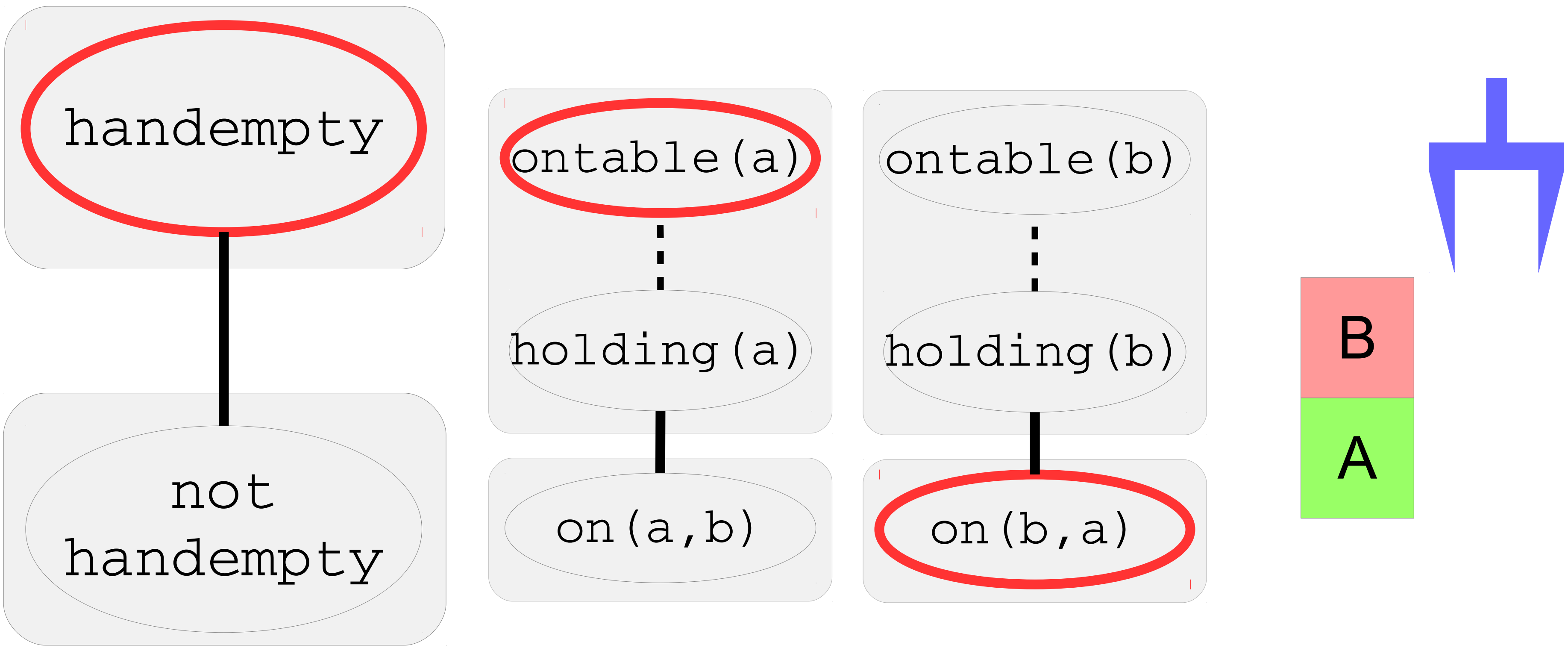


Grey squares are the abstract features generated by GreedyAFG

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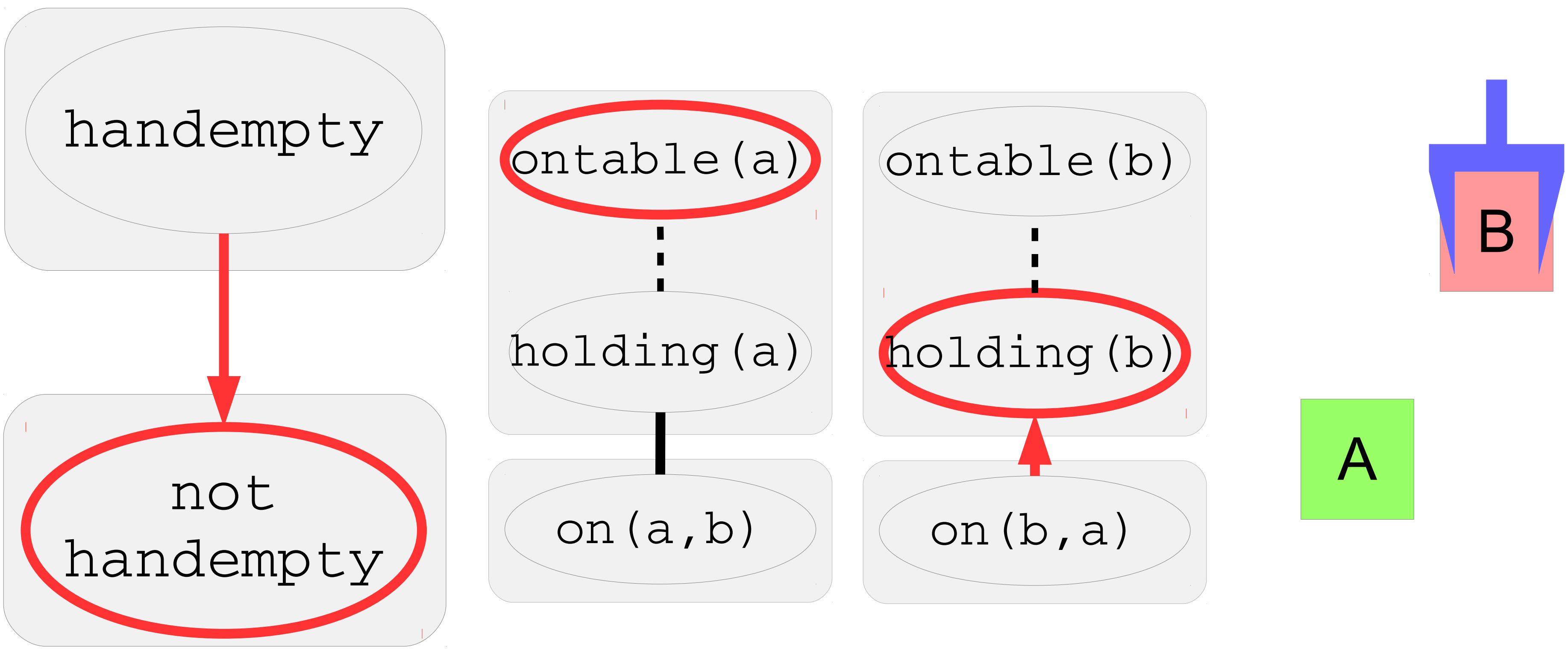


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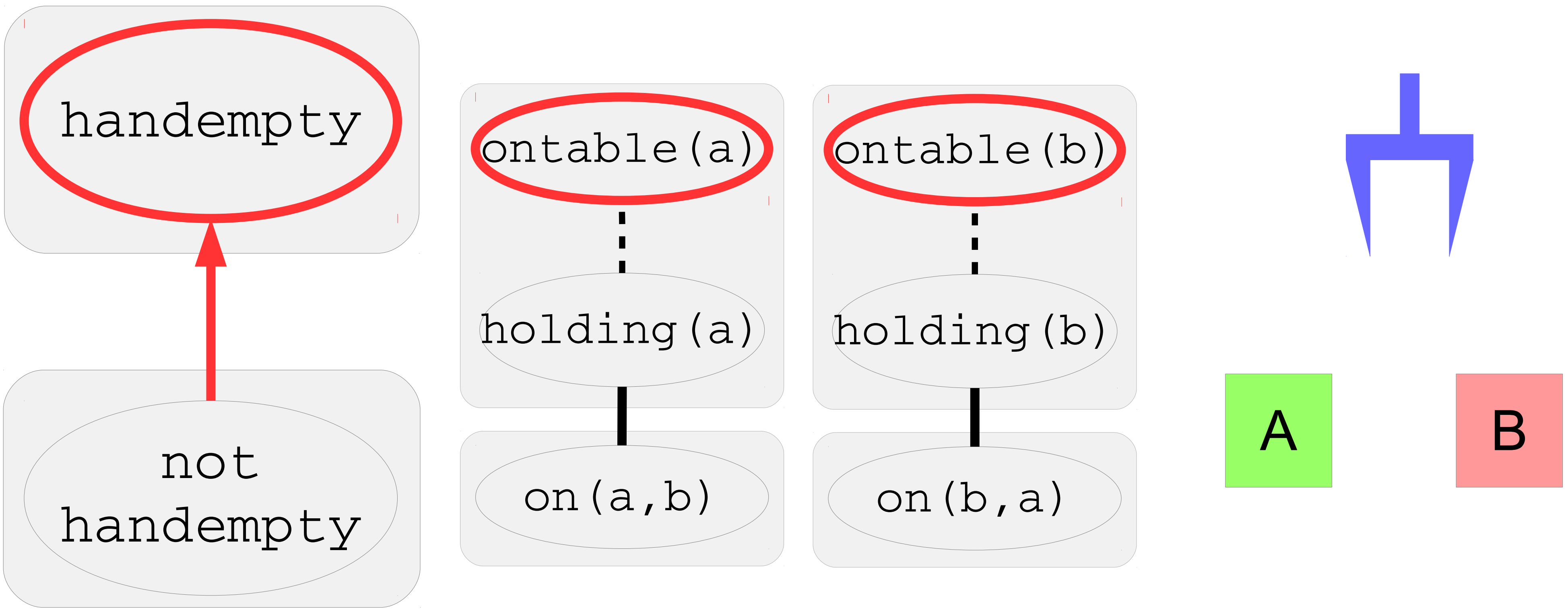


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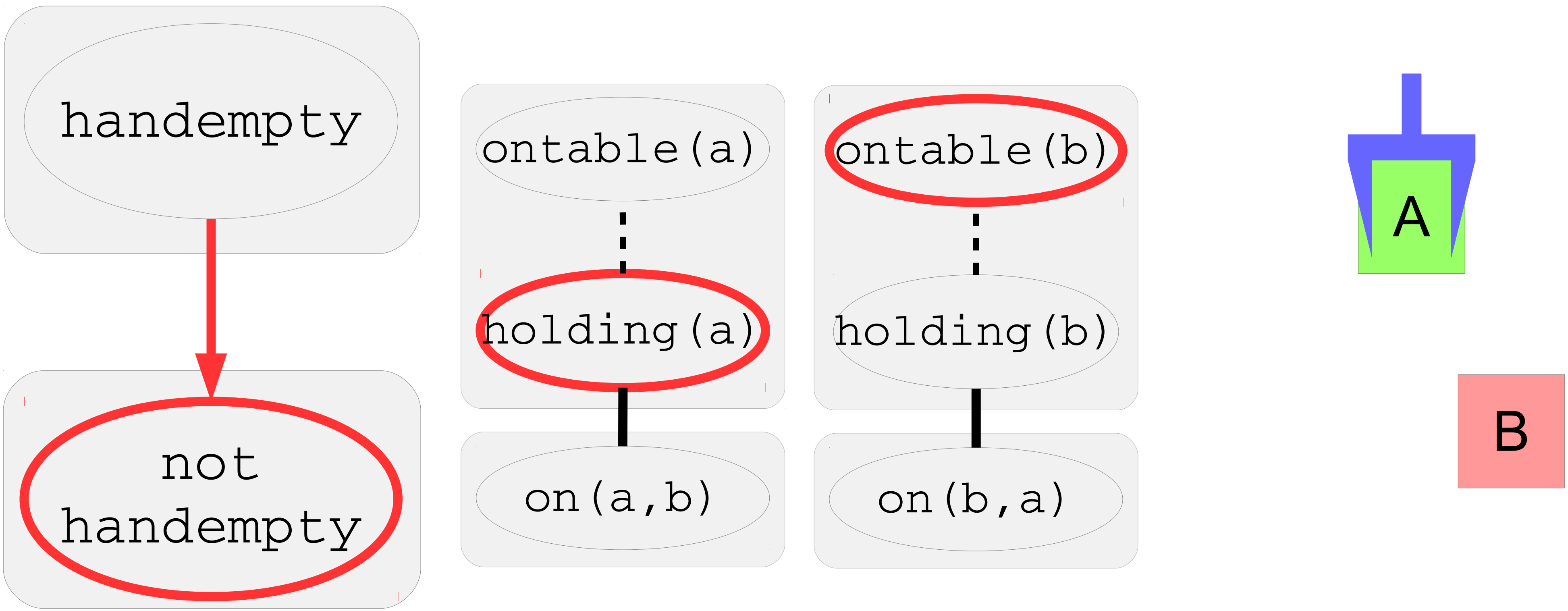


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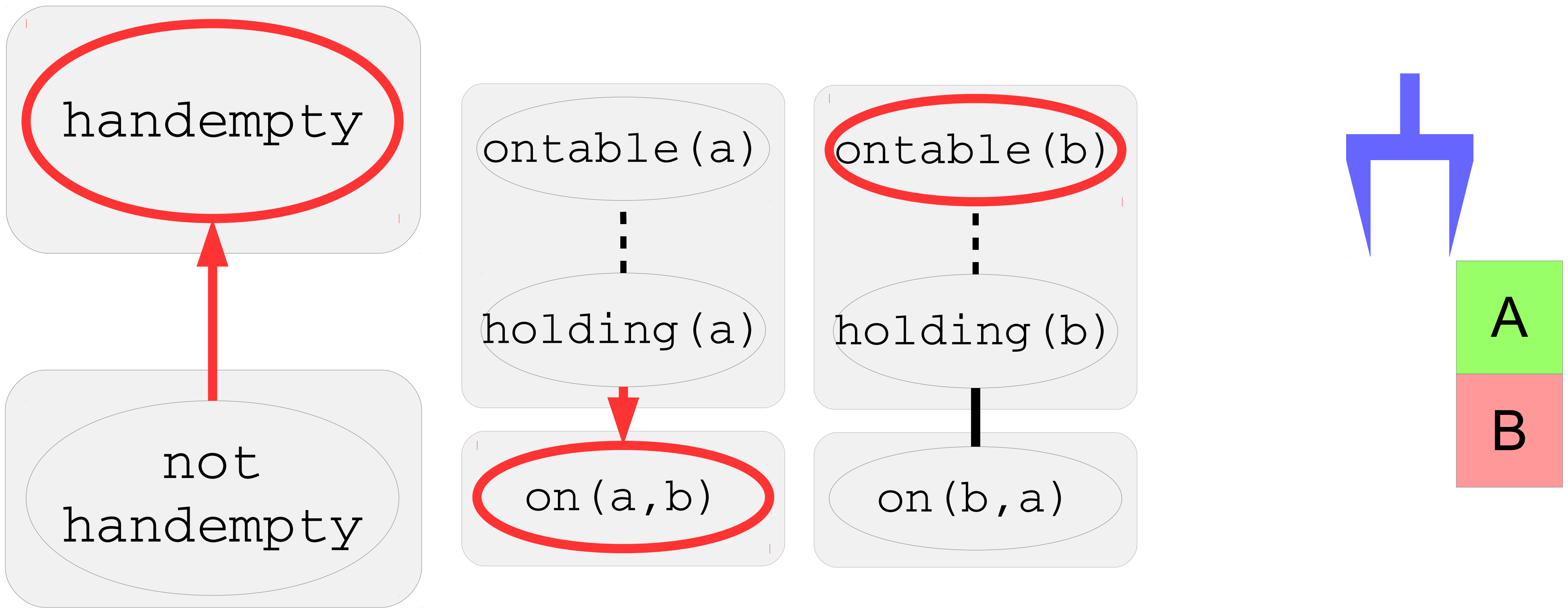


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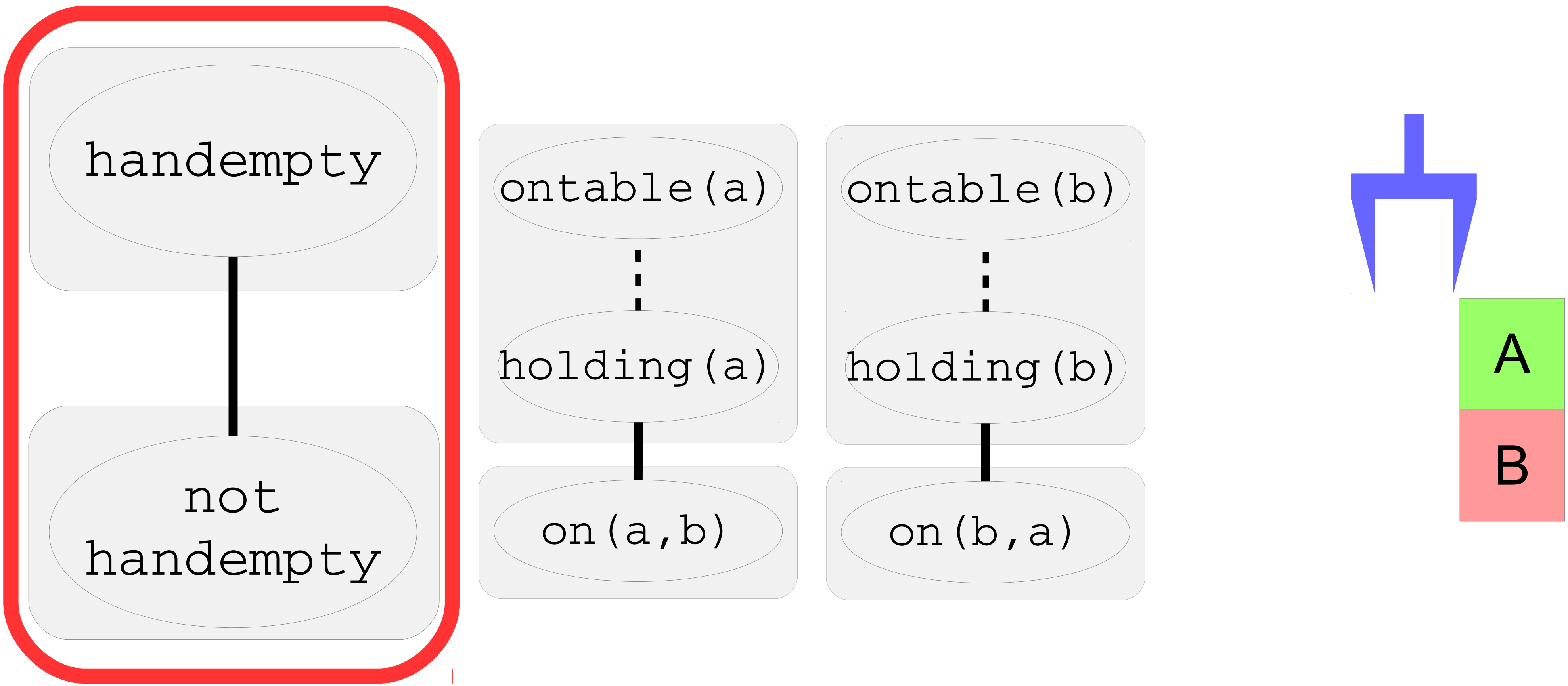
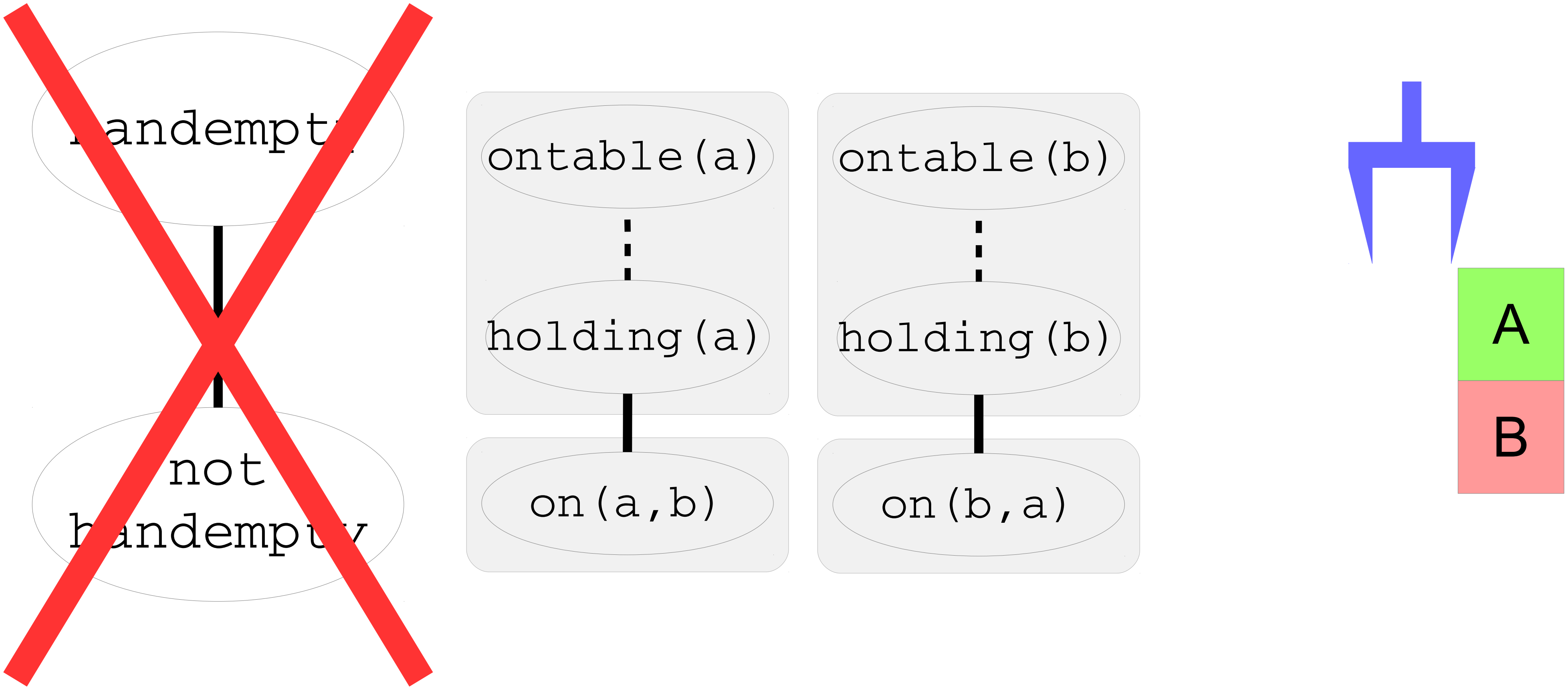



This abstract feature ALWAYS changes its value!
Thus ALL node generations may incur communication overhead!

# Fluency-Based Filtering

- We propose *Fluency-based filtering* which ignores features which change their values too frequently
- We apply GreedyAFG to the rest of the features

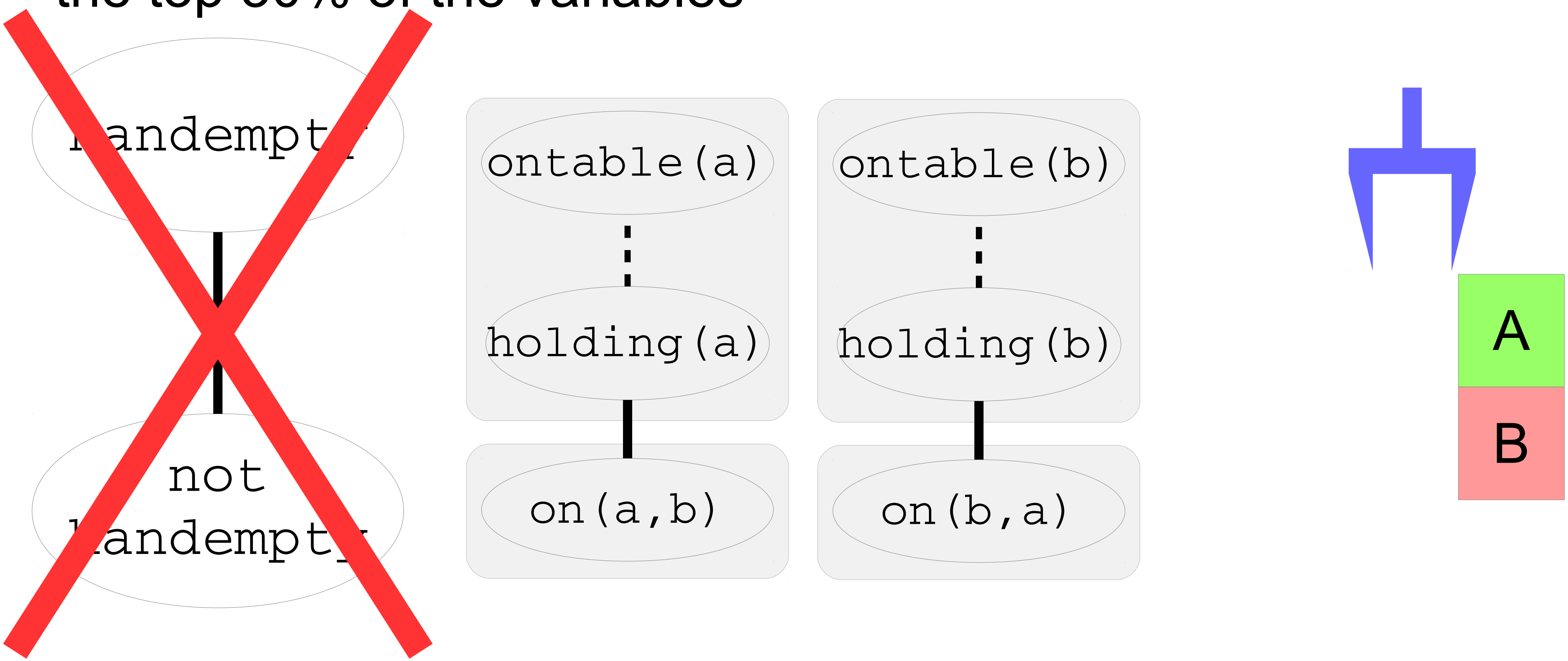


# Fluency-Based Filtering

- We define *fluency* of a variable $x$

$$fluency(x) := \frac{number\ of\ ground\ actions\ which\ change\ the\ value\ of\ x}{total\ number\ of\ ground\ actions}$$

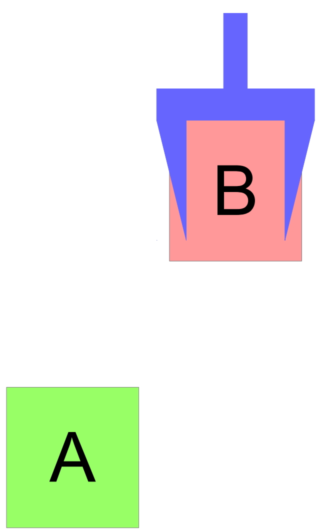
- Our implementation ignores variables whose fluency is in the top 30% of the variables



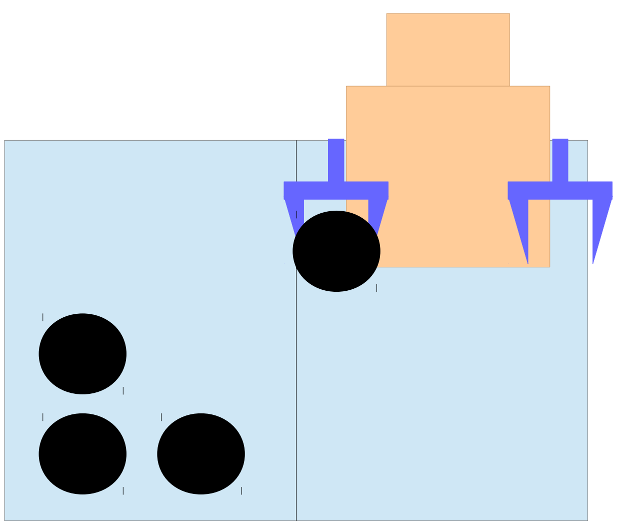

$fluency(x_0) = 1.0$ $fluency(x_1) = 0.5$ $fluency(x_2) = 0.5$

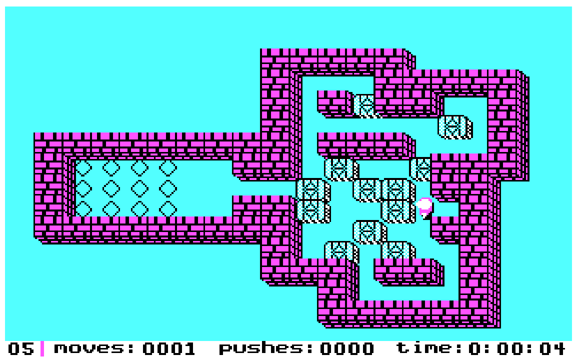
# Fluency-Based Filtering

- In fact, variables with high fluency are common in wide range of domains
- For example, in domains modeling agent-environment, variables modeling the state of agents tend to have high fluency



blocks world

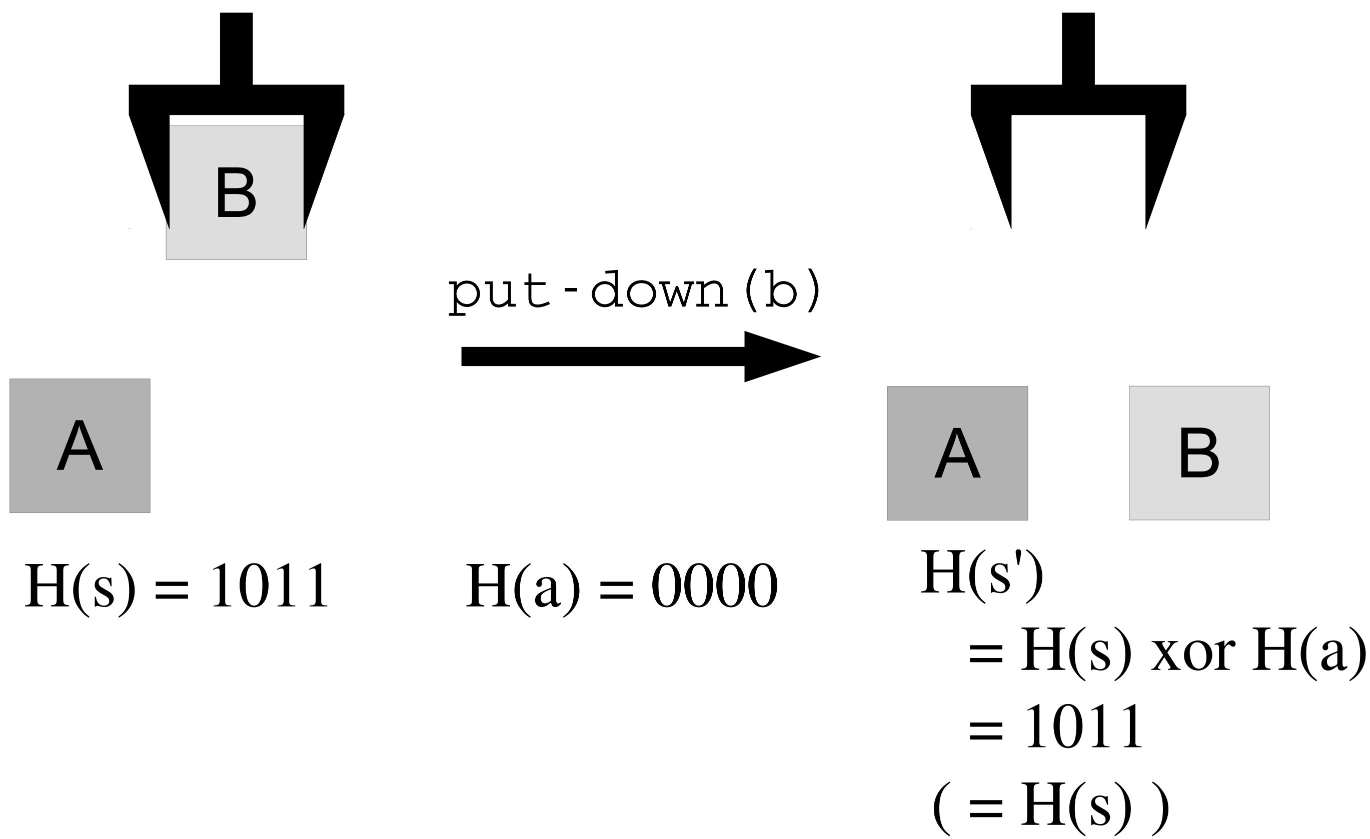

gripper



sokoban

# Operator-based Zobrist hashing

- Zobrist hashing incurs significant communication overhead
- Method: Preinitialize the random table so that the given operator does not change the hash value



# Dynamic AHDA*

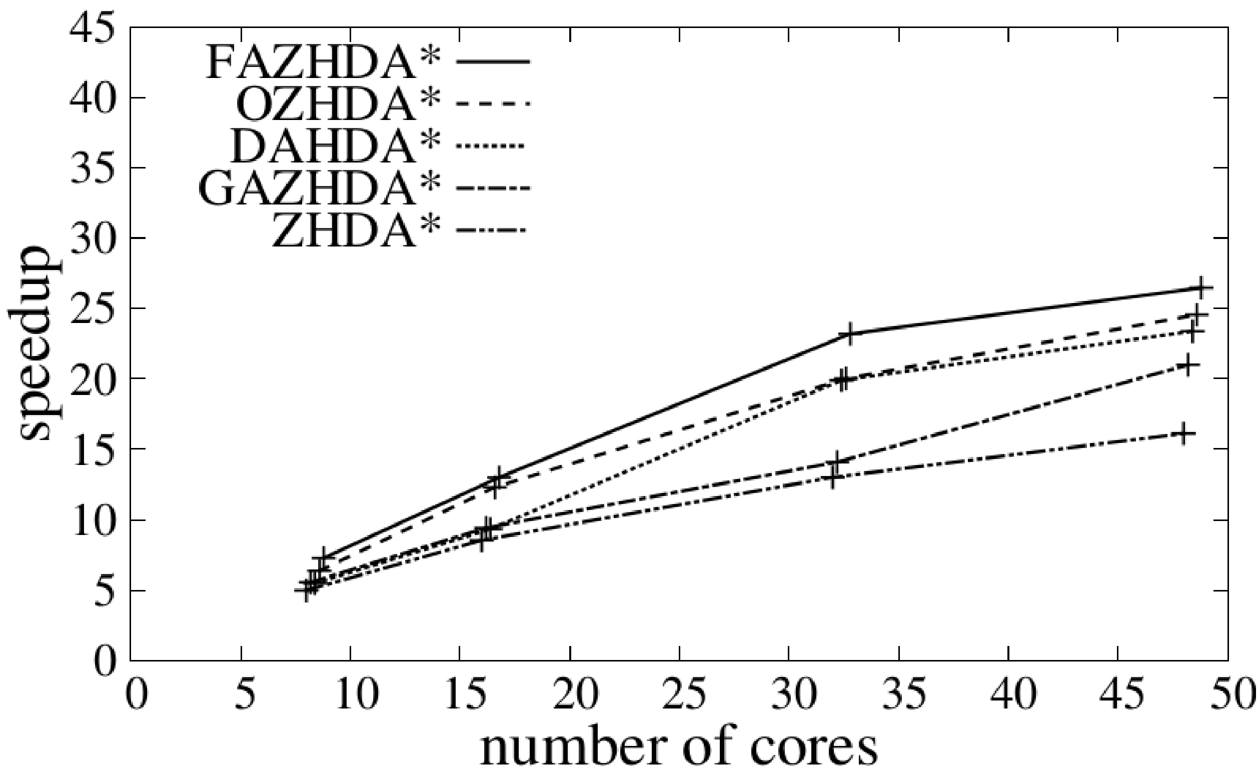
- In previous work, AHDA* used a fix threshold to the number of the abstract nodes
- This leads to suboptimal performance to instance set with varying difficulity (especially in distributed memory cluster)
- Dynamic AHDA* set the threshold according to the size of the problem difficulty
- Our current implementation set the threshold of the total number of features in the abstract state space to be 30% of the total number of features in the problem instance

# Experiments

- We evaluated HDA* variants on IPC benchmarks (21 instances)
- 48 cores (6 machines with 8 cores)
- Based on FastDownward and MPICH3
- merge&shrink heuristic (LFPA)

# Experiments

- FAZHDA*: AZHDA* using GreedyAFG with fluency filtering
- OZHDA*: Operator-based Zobrist hashing
- DAHDA*: Dynamic AHDA*
- GAZHDA*: AZHDA* using GreedyAFG without fluency filtering




→**FAZHDA* outperformed GAZHDA* and other HDA* variants**

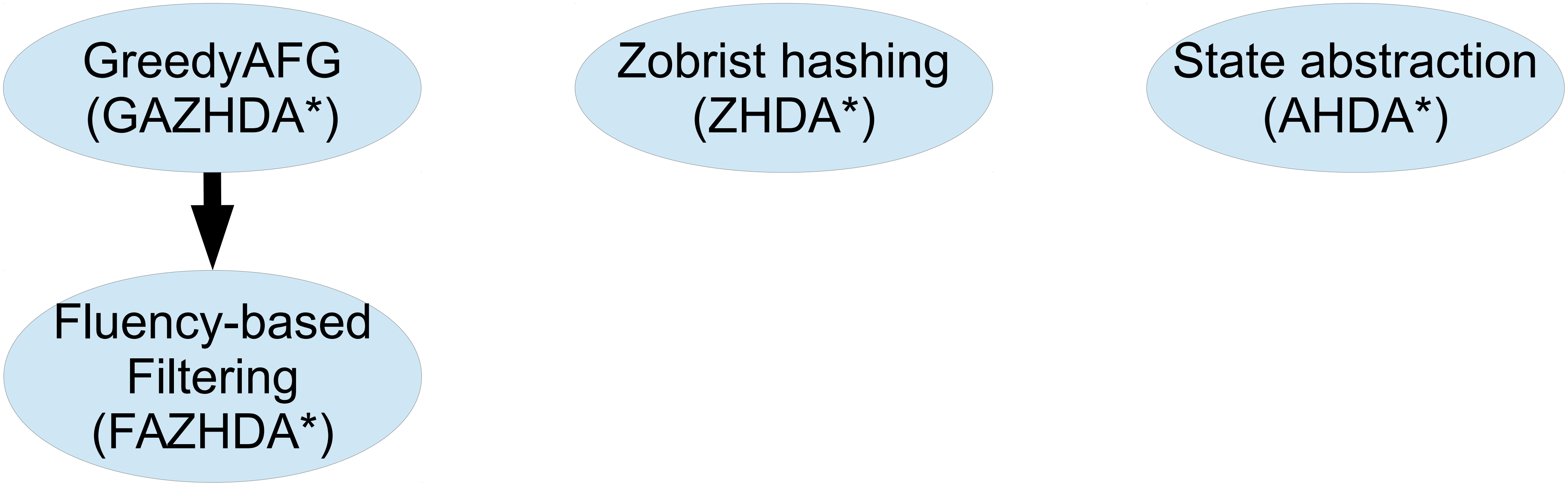
# Summary of Paper

GreedyAFG
(GAZHDA*)

Zobrist hashing
(ZHDA*)

State abstraction
(AHDA*)

# Summary of Paper

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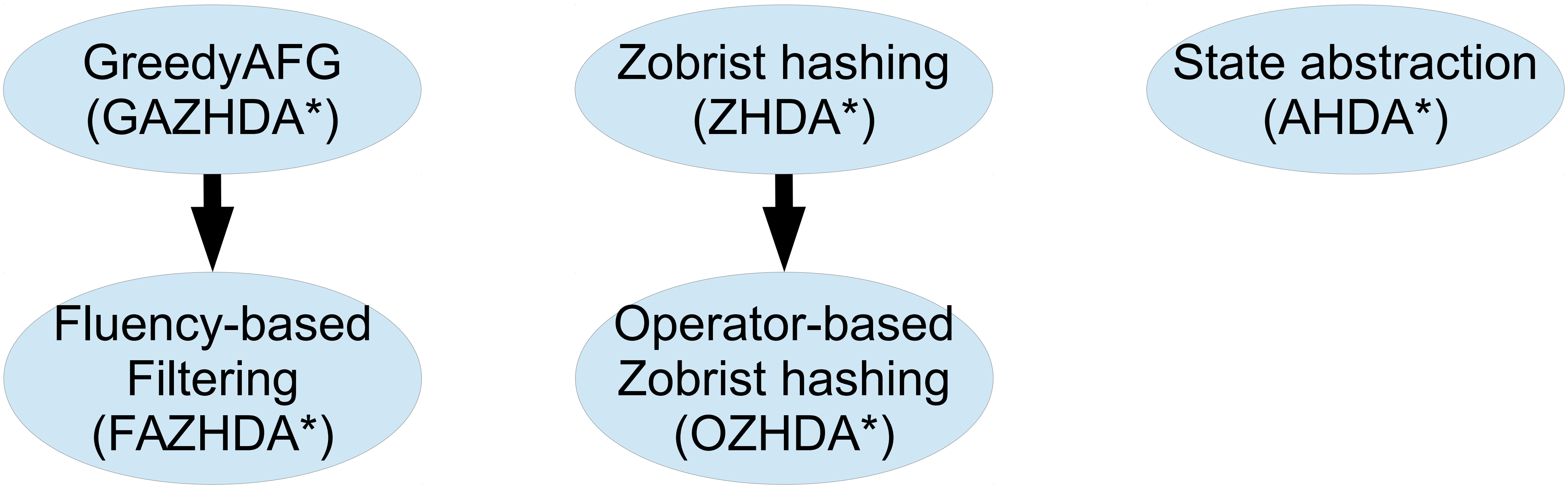
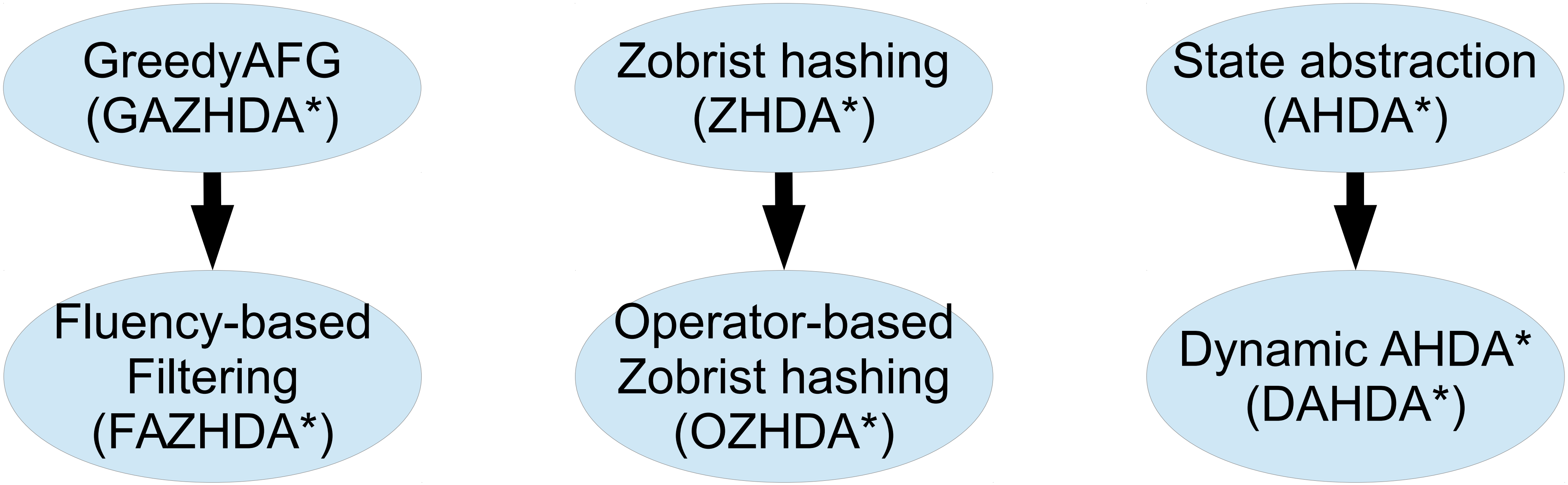



- We proposed Fluency-based filtering for AZHDA* which ignores variables which frequently change their values
- We proposed Operator-based Zobrist hashing which generate Zobrist hashing bitstrings that ensures reduced communication overhead

# Summary of Paper




- We proposed Fluency-based filtering for AZHDA* which ignores variables which frequently change their values
- We proposed Operator-based Zobrist hashing which generate Zobrist hashing bitstrings that ensures reduced communication overhead
- We implemented Dynamic AHDA* to determine the size of abstract state space according to the instance difficulty

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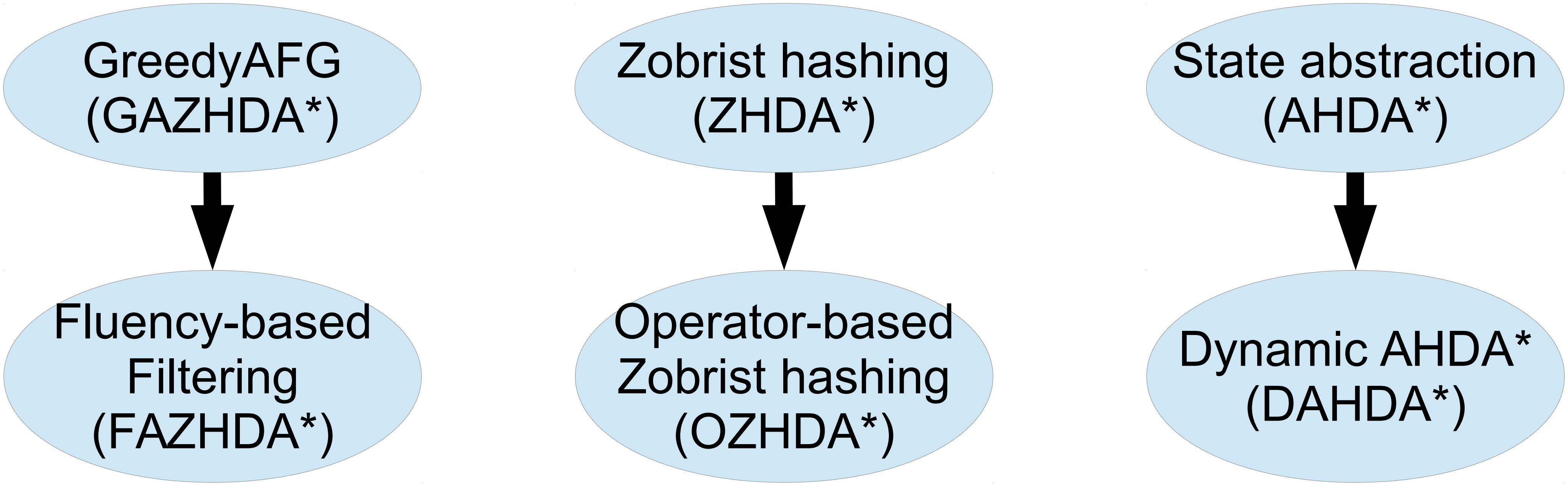


- We proposed Fluency-based filtering for AZHDA* which ignores variables which frequently change their values
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- We implemented Dynamic AHDA* to determine the size of abstract state space according to the instance difficulty
- AZHDA*+Fluency-based filtering performed the best

# Operator-based Zobrist hashing

$Z(s)$ = $R[x_1]$ xor $R[x_2]$ xor ... xor $R[x_n]$

- Let $s$' be the child node of $s$ using operator $a$
- Assume all effects in add&delete effect take place
- Zobrist hash value of s' is

$Z(s')$ = $Z(a)$ xor $Z(s)$

where $Z(a)$ = $R[p_1]$ xor $R[p_1]$ xor … xor $R[p_1]$ for all propositions $p_i$ in add&delete effect in $a$

**→If $Z(a)$ = 0, then $Z(s')$ = $Z(s)$**

# Operator-based Zobrist hashing

$$Z(s) = R_1[x_1] \text{ xor } R_2[x_2] \text{ xor ... xor } R_n[x_n]$$

**→If $Z(a)$ = 0, then $Z(s')$ = $Z(s)$**

1. Select one operator

2. Modify a value of $R_i[x_i]$ value without a flag so that **$Z(a)$ = 0**

3. Set flags to all propositions in a so that they won't be modified later

4. Repeat from 1

- We select the operator with least preconditions (future work)

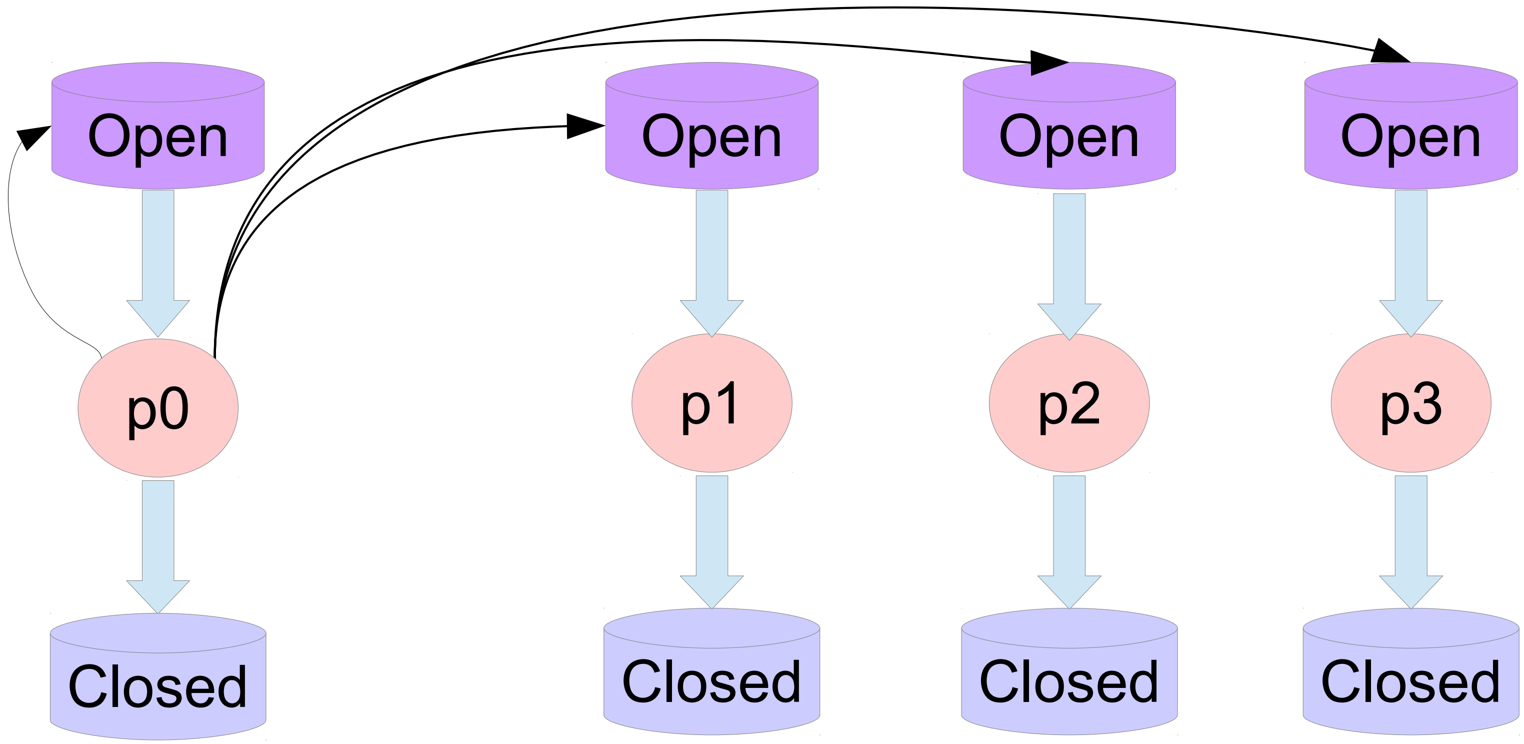
# Dynamic AHDA* construction

- Follows the construction of Structured Duplicate Detection (SDD) (Zhou&Hansen 2007)
- Idea: Add an atom group which preserve the locality the best

- Select an atom group (= SAS+ variable) which retains the maximum-degree of the abstract state graph smallest compared to the graph size
- Add the atom group into the abstract state representation
- Terminate if the size of the abstract state reaches a threshold Nmax
- Abstract state is represented using the selected atom groups, and the projection from a state to an abstract state simple ignores all features not in the atom groups

# Hash Distributed A* (HDA*)

Kishimoto, Fukunaga, & Botea (2009)




- Each thread has its own open/closed list
- Each thread sends generated nodes to its owner (assigned by the hash function)
- Other than sending/recieving each thread runs A* search

# Summary of Paper

- GreedyAFG generates abstract features for Abstract Zobrist hashing but fails to reduce communication overhead due to variables with high fluency
- We introduced a notation of fluency and proposed Fluency-based filtering which ignores variables which frequently change their values
- We proposed Operator-based Zobrist hashing which generate Zobrist hashing bitstrings that ensures reduced communication overhead
- We implemented Dynamic AHDA* to determine the size of abstract state space according to the instance difficulity
- AZHDA*+Fluency-based filtering performed the best

# $eff_{esti}$ vs. efficiency

- We define a metric to estimate the walltime efficiency *$eff_{esti}$* and actual walltime efficiency

$$eff_{esti} := \frac{1}{(1 + cCO)(1 + SO)}$$