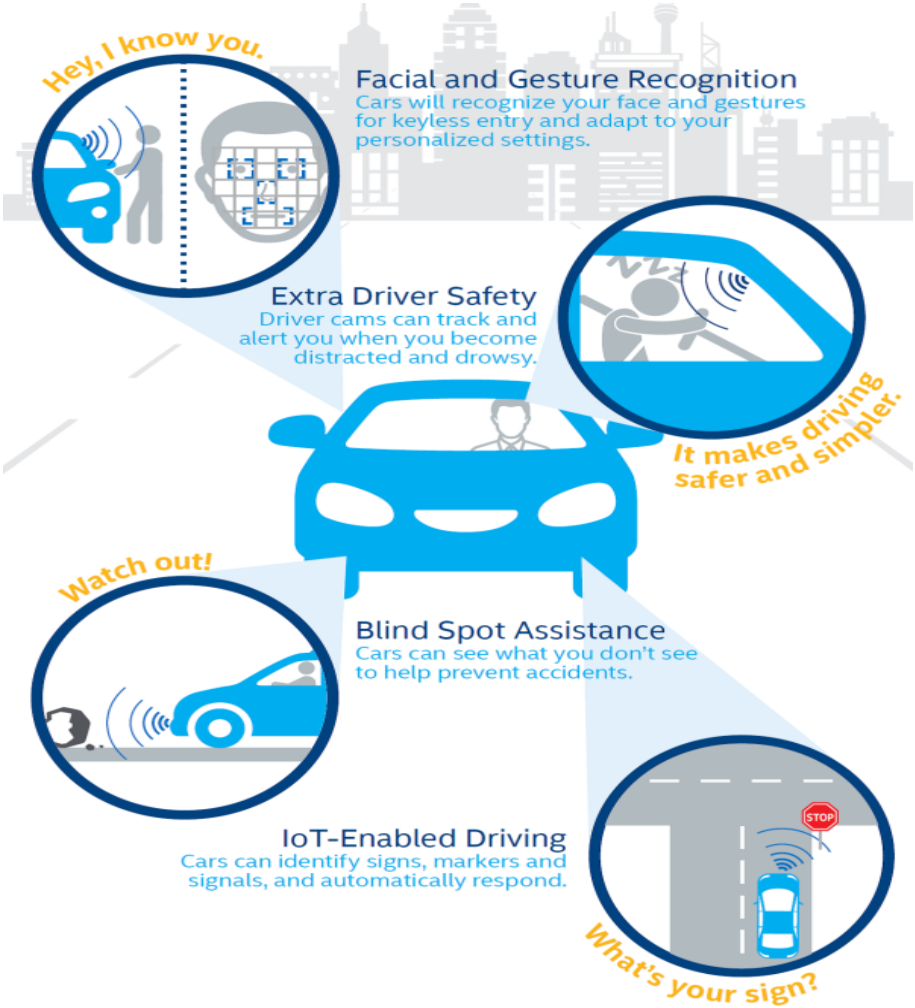
PARALLEL Q-LEARNING FOR IOT ENVIROMENTS

MIGUEL CAMELO, JEROEN FAMAEY AND STEVEN LATRÉ

MANY IOT APPLICATIONS REQUIRE ADAPTIVE AND SMART CONTROL….



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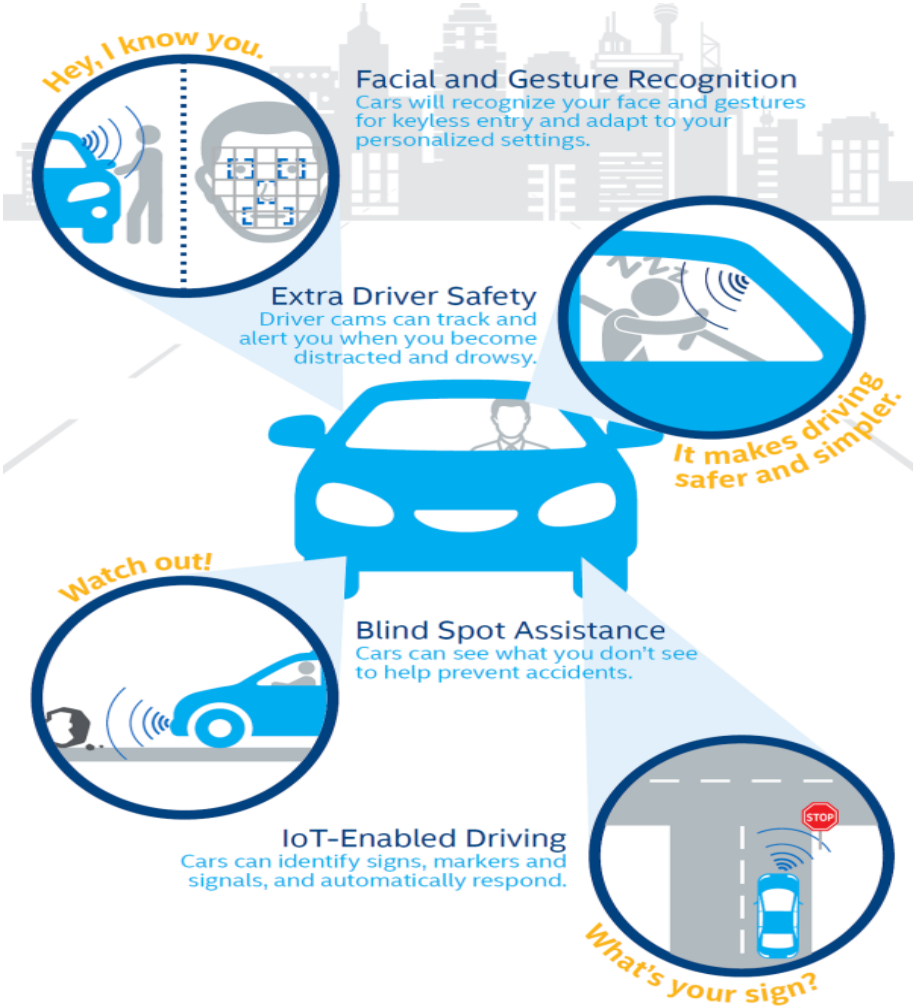
MANY IOT APPLICATIONS REQUIRE ADAPTIVE AND SMART CONTROL…. WITH LOW LATENCY



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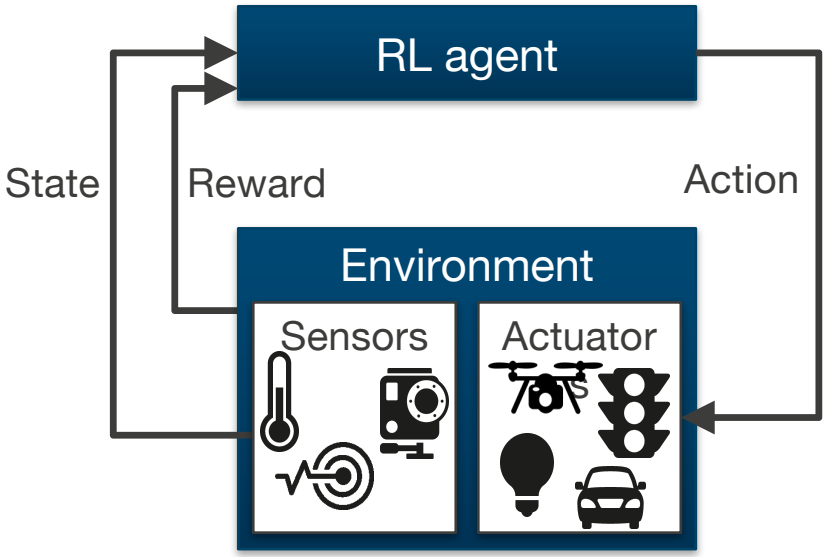
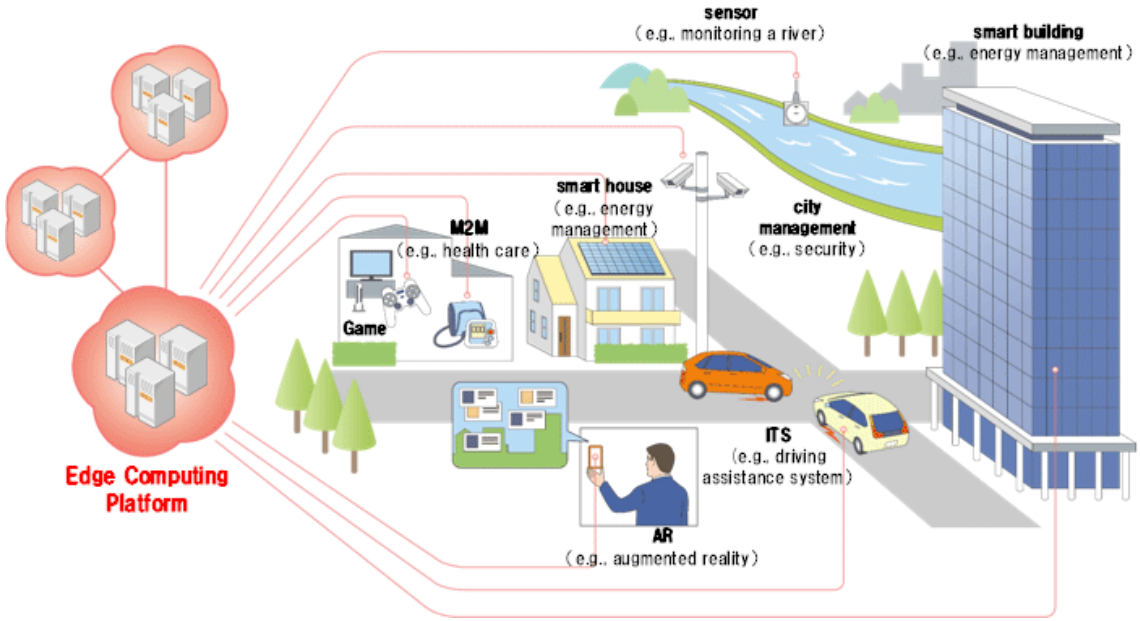
RL AS A MEANS TO CONTROL IOT DEVICES





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PARALLEL Q-LEARNING FOR CONSTRAINED COMPUTING ENVIRONMENTS

Q-Learning (QL): Strengths and weaknesses

Traditional Parallel QL: the need of a new model for PQL

PQL with co-allocation of processing and data

Performance evaluation

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Q-LEARNING (QL) IS A SIMPLE AND EFFICIENT RL ALGORITHM

Model free RL -> No previous information of the environment is needed.

Guarantee of convergence if tabular representation of Q-values.

Initialize Q(s, a) arbitrarily

1. Repeat (for each episode):
2. Initialize s
3. Repeat (for each iteration inside of the episode):
4. Choose a from s using policy derived from Q (e.g. ε-greedy)
5. Take action a, observe r, s'
6. $Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$
7. $s \leftarrow s'$
8. Until s is terminal

S/A	a_1	a_2	a_3	...	a_n
s_1	$Q(s_1, a_1)$	$Q(s_2, a_2)$	$Q(s_3, a_3)$	...	$Q(s_1, a_n)$
s_2	$Q(s_2, a_1)$	$Q(s_2, a_2)$	$Q(s_2, a_3)$	...	$Q(s_2, a_n)$
s_3	$Q(s_3, a_1)$	$Q(s_3, a_2)$	$Q(s_3, a_3)$	...	$Q(s_3, a_n)$
....	...	...	...	...	...
s_m	$Q(s_m, a_3)$	$Q(s_m, a_3)$	$Q(s_m, a_3)$	...	$Q(s_m, a_n)$

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MOST OF RL ALGORITHMS (INCLUDING QL) HAVE THREE MAIN LIMITATIONS

Sequential and designed for centralized environments.

Requires long training time to learn optimal policy.

Table-based algorithms have scalability issues in large scale problems.

PARALLEL QL AND COLLABORATIVE MA-QL REDUCE THE TRAINING TIME

Collaborative Multi-agent (MA) QL

- A unique environment is altered by actions of agents.
- Agents need to coordinate actions.

Parallel QL

- All agents learn same task
- Episodes can be reduced in a factor of 1/n
- There is guarantee of convergence

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Both approaches allow decentralized implementation

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FUNCTION APPROXIMATORS (E.G. NEURONAL NETWORKS) DO NOT GUARANTEE CONVERGENCE

Neuronal Networks:

- Provide a compact representation of the Q-Table
- Allow solving problems with large number of states.

Neuronal Networks **do not**:

- Guarantee convergence.
- Provide simple and intuitive implementation.
- Slower to find optimal policy than table-based approach.

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We need to go back to table-based approaches

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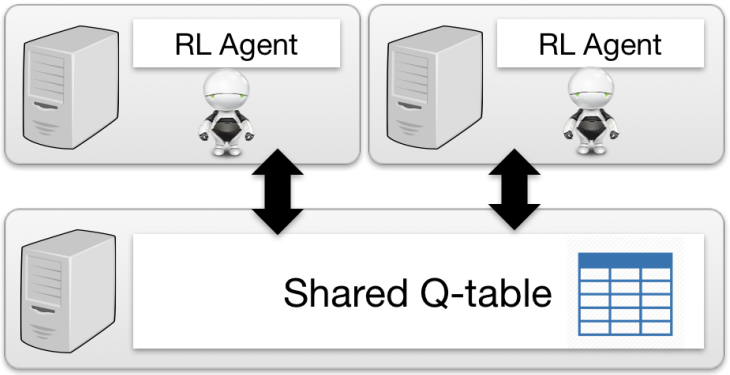
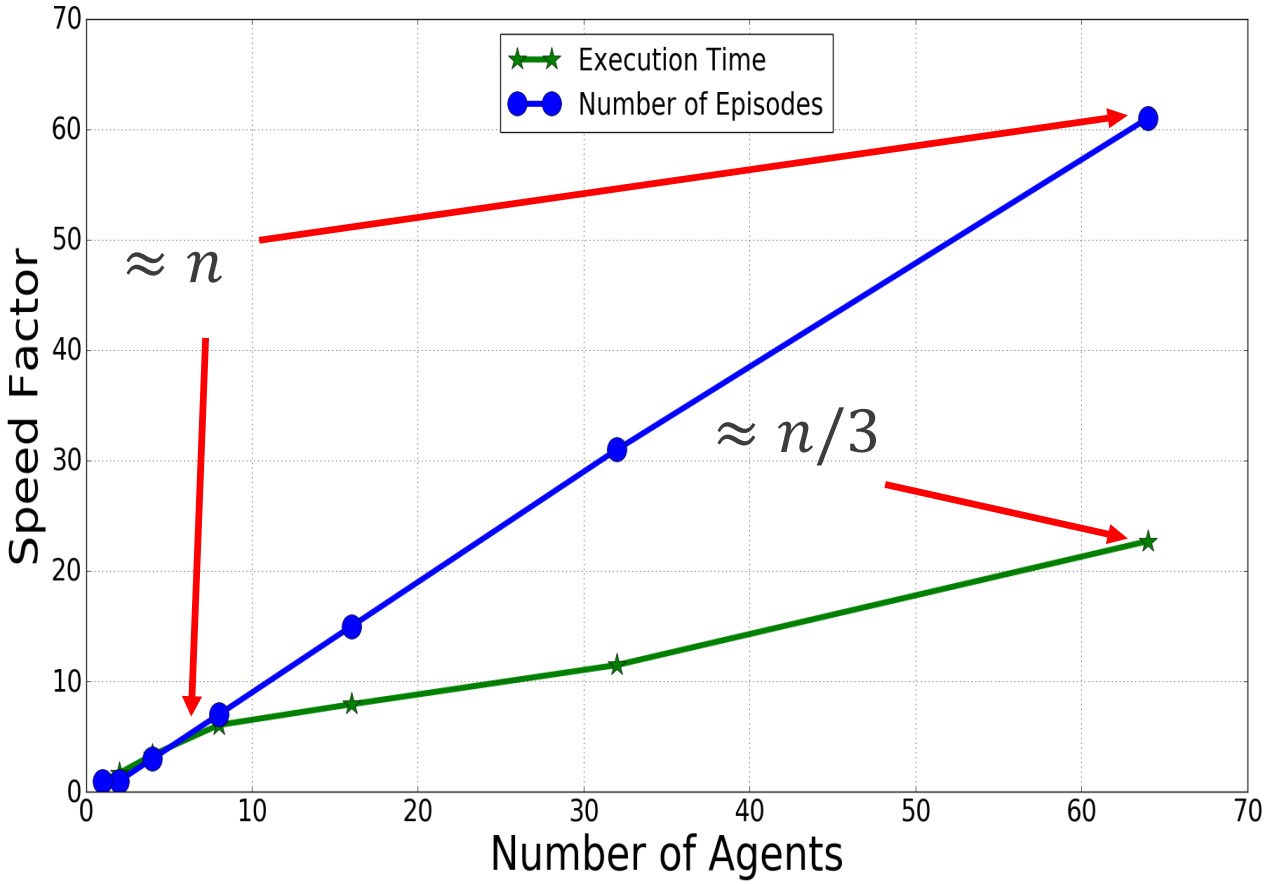
TRADITIONAL PQL: CENTRAL QT BOTTLENECK WITH HIGH-COST COMMUNICATION SCHEME



Constant Share RL algorithm with centralized table



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A MA-RL MODEL BASED ON FUNCTIONS PROVIDES THE FLEXIBILITY THAT WE NEED

Many MA-RL algorithms (including PQL) execute several (underlying) tasks while they are running

- Allocation of resources.
- Creation and deployment of RL agents.
- Synchronization among agents.
- Data collection.
- Execution of RL algorithm.
- Management of QT.

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Function	
Management	▪ Allocation of resources. ▪ Creation and deployment of RL agents. ▪ Synchronization among agents. ▪ Data collection.
Processing	▪ Execution of RL algorithm.
Storage	▪ Management of QT.

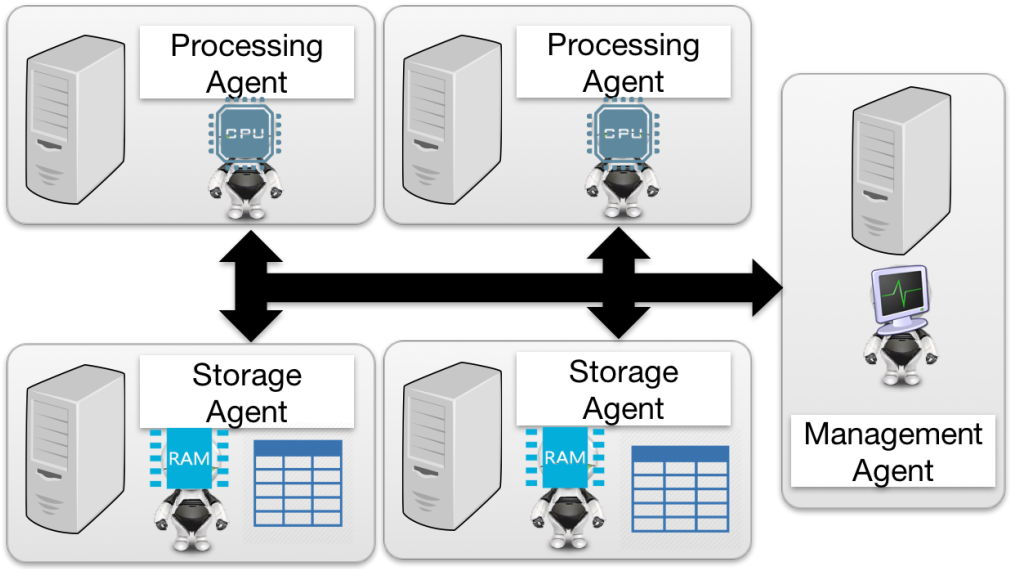
EACH FUNCTION IS ASSIGNED TO A SPECIFIC KIND OF AGENT

Processing agent (PrA)

- This is a QL agent that works on a (possible external) QT.

Storage Agent (StA)

- It stores (part of) the QT.
- It serves requests from PrA.



Constant Share RL algorithm modeled as a function of management, storage and processing agent

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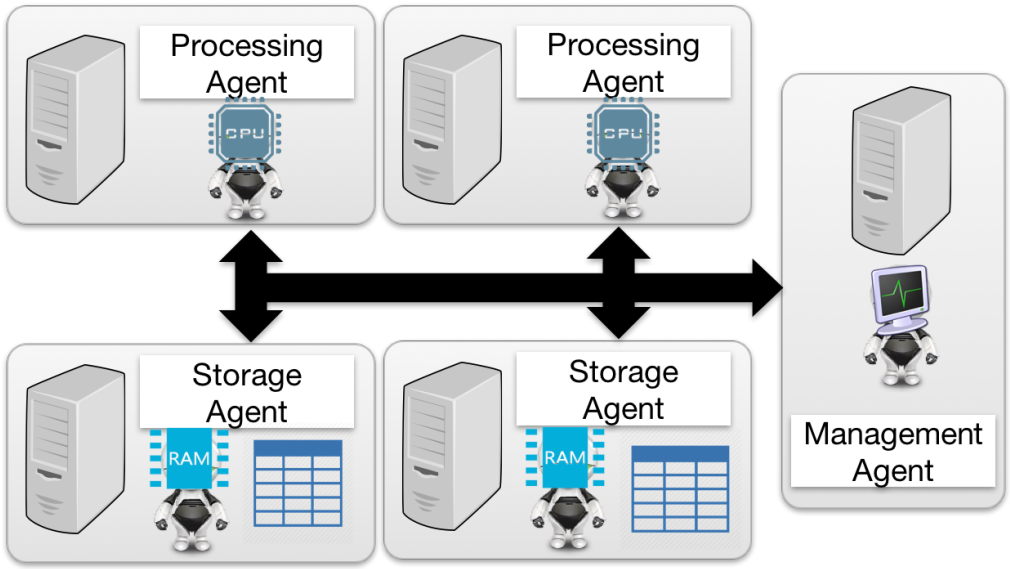
EACH FUNCTION IS ASSIGNED TO A SPECIFIC KIND OF AGENT

Management agent (MngtA)

- Deploy StAs on available storage resources.
- Build and distributed QT among StAs.
- Deploy PrA on available processing resources.



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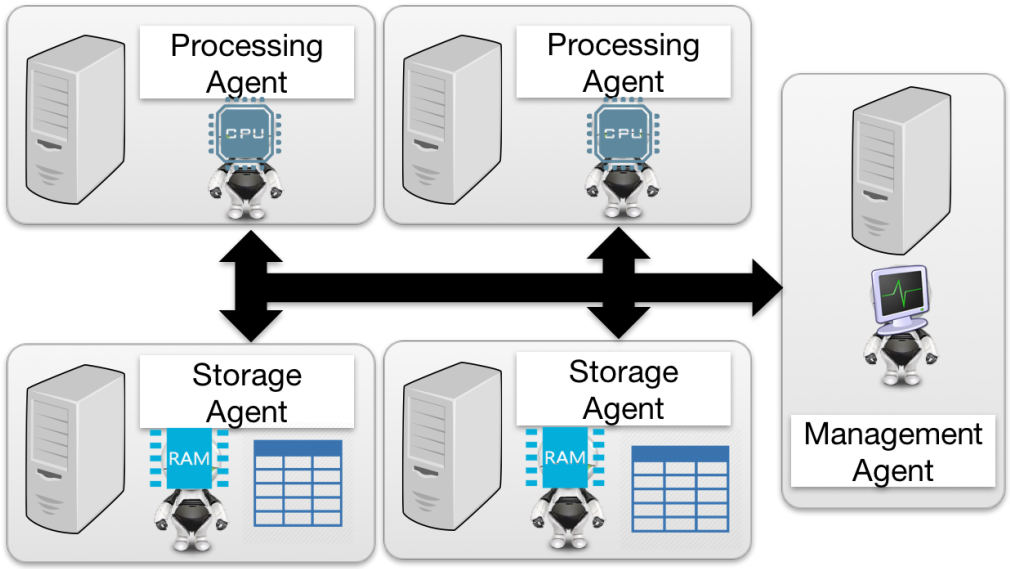
THE NEW MULTI-AGENT MODEL ALLOWS A COMPLETE DECENTRALIZED EXECUTION

Applicable to many MA-RL algorithm

QT is not a bottleneck anymore

It can guarantee convergence



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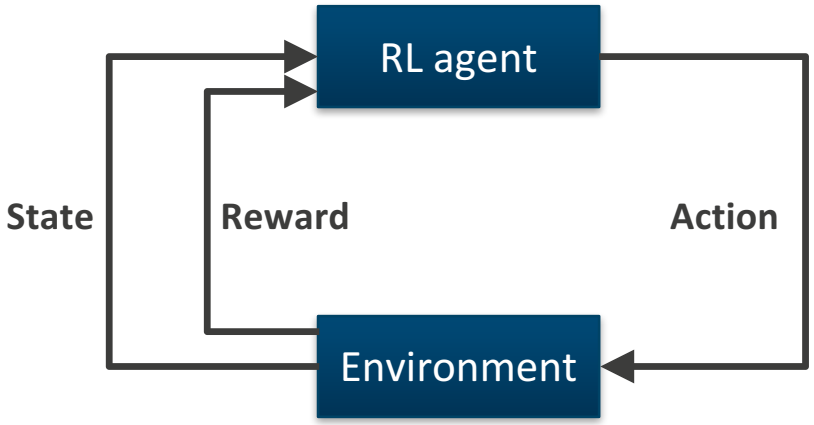
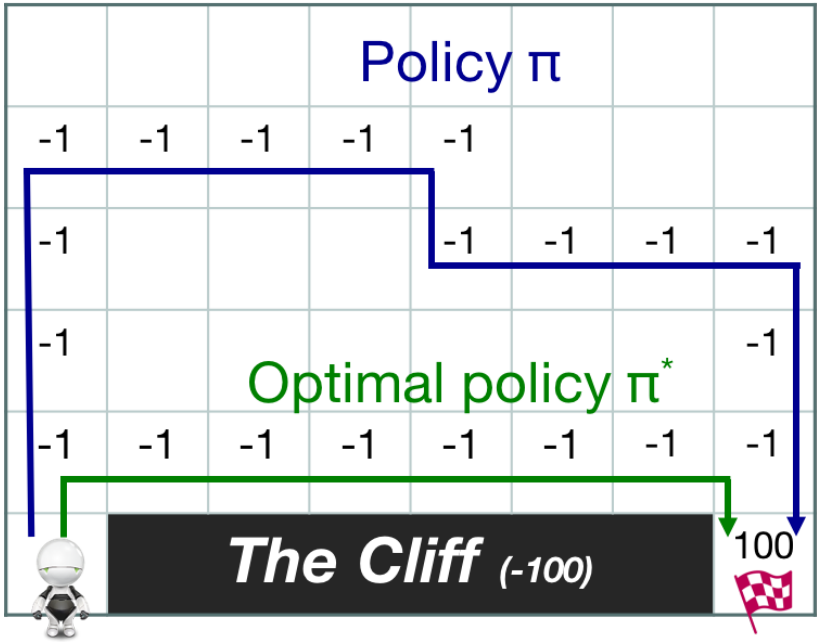
EXAMPLE: THE CLIFF PROBLEM

- Goal: The agent navigates a grid from start to goal without falling into the cliff.

Reward function:
- -100 if robot falls into the cliff
- -1 for each movement of the robot
- +100 if robot reaches the goal





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PCSP : PQL WITH CO-ALLOCATION OF STORAGE AND PROCESSING

Two main procedures:

- Creation and deployment of agents
- QL execution

Algorithm 2 PQL with Co-allocation of Storage and Processing (PCSP)

Require: Number of states $|S|$ and actions $|A|$,
Require: Set of physical nodes M
1: **if** $|M| > 0$ **then**
2: Deploy a MngtA
3: $q \leftarrow$ total available memory across physical nodes.
4: **if** $O(|S||A|) \leq q$ **then**
5: Compute table partitions P
6: Deploy $n_s = |P|$ StA
7: Initialize the QT
8: Create and deploy n_p PrA
9: **while** p has not converged, $\forall p \in PrA$ **do**
10: Execute QL on p, $\forall p \in PrA$
11: **end while**
12: Obtain statics from p, $\forall p \in PrA$
13: Retrieve the optimal policy π from QT
14: **end if**
15: **end if**
16: **return** π

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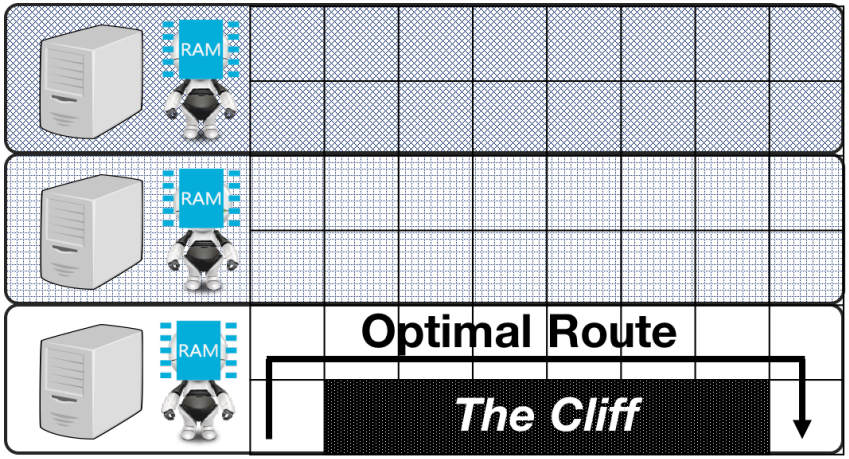
STORE CONSECUTIVES STATES IN THE SAME STA REDUCES THE COMMUNICATION COST



Two states s and s' are consecutives if s' is the next state of s' after execution some action.

Operations such as $\max_{a'} Q(s', a')$ are completely local.

States of a (possible optimal) solution are managed by a few (maybe unique) StAs.

THE NUMBER OF STATES STORED PER NODE IS WELL-BALANCED ACROSS THE RESOURCES

n_s (number of StAs) $= P$ (number of partitions)

$P = \left\lceil \frac{c}{2} \right\rceil$, c is the total processing resources.

In homogeneous environments StA stores $\frac{|S||A|}{n_s}$

In heterogeneous environments each StA i stores s_i bits

$$\sum_{i=1}^{n_S} s_i = \Omega(|S||A|), 0 \leq s_i \leq |S||A|$$

EXPLOIT THE STORAGE OF CONSECUTIVES STATES BY DEPLOYING PRA NEXT TO STA

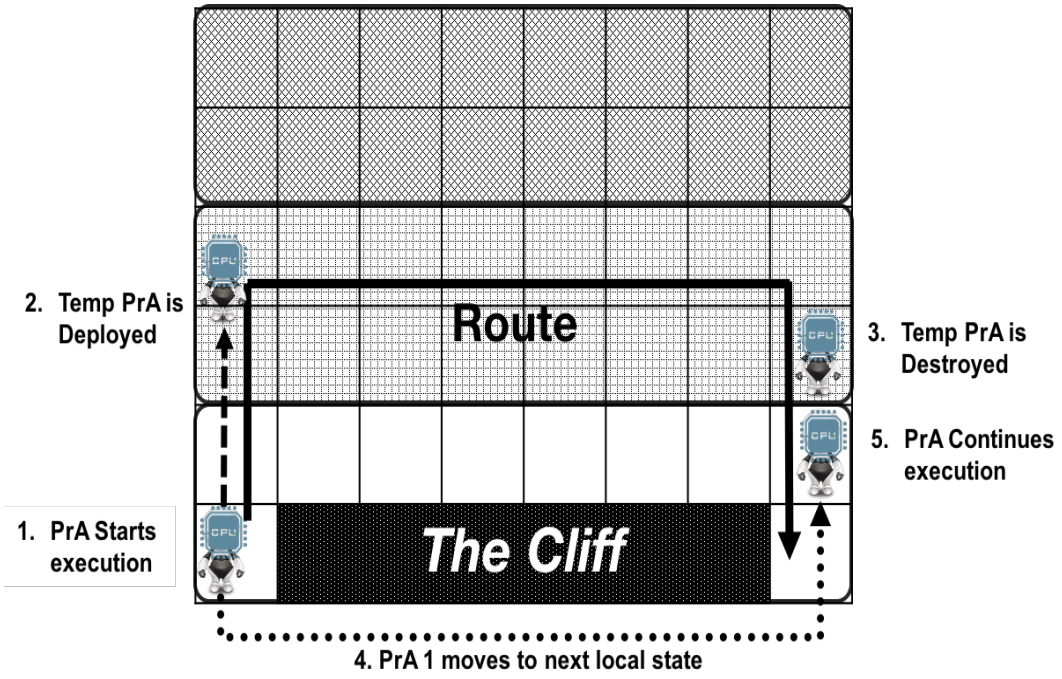
Deploy PrAs on nodes where StA have been already deployed

n_p (number of PrAs) = n_s (number of StAs)

Minimum communication cost if PrA is exploring states managed by the co-allocated StA

In case of requiring states from remote StAs, a temporal PrA is deployed

DEPLOYING TEMPORAL PRA MINIMIZES NUMBER OF REQUESTS FROM ORIGINAL PRA TO REMOTE STAS.



Algorithm 3 Modified Q-Learning

Require: Access to Distributed Q-Table with $|S||A|$ values

repeat(for each episode)
  Initialize s
  repeat(for each iteration)
    Use behavior policy to choose a
    Take action a, observe r, s'
    if s' is not stored in any local StA **then**
      Deploy temp PrA on node where s' is stored.
      repeat
        Wait
      until temp PrA has finished
      $s \leftarrow s'$
    else
      $TDerror = \max_{a'} Q(s', a') - Q(s, a)$
      $Q(s, a) \leftarrow Q(s, a) + \alpha \cdot (r + \gamma \cdot TDerror)$
      $s \leftarrow s'$
    end if
  until s is goal state
until max episodes = true or convergence = true

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WE EVALUATED PCSP AGAINST SEVERAL QL ALGORITHMS UNDER TWO METRICS (EPISODES AND EXECUTION TIME)

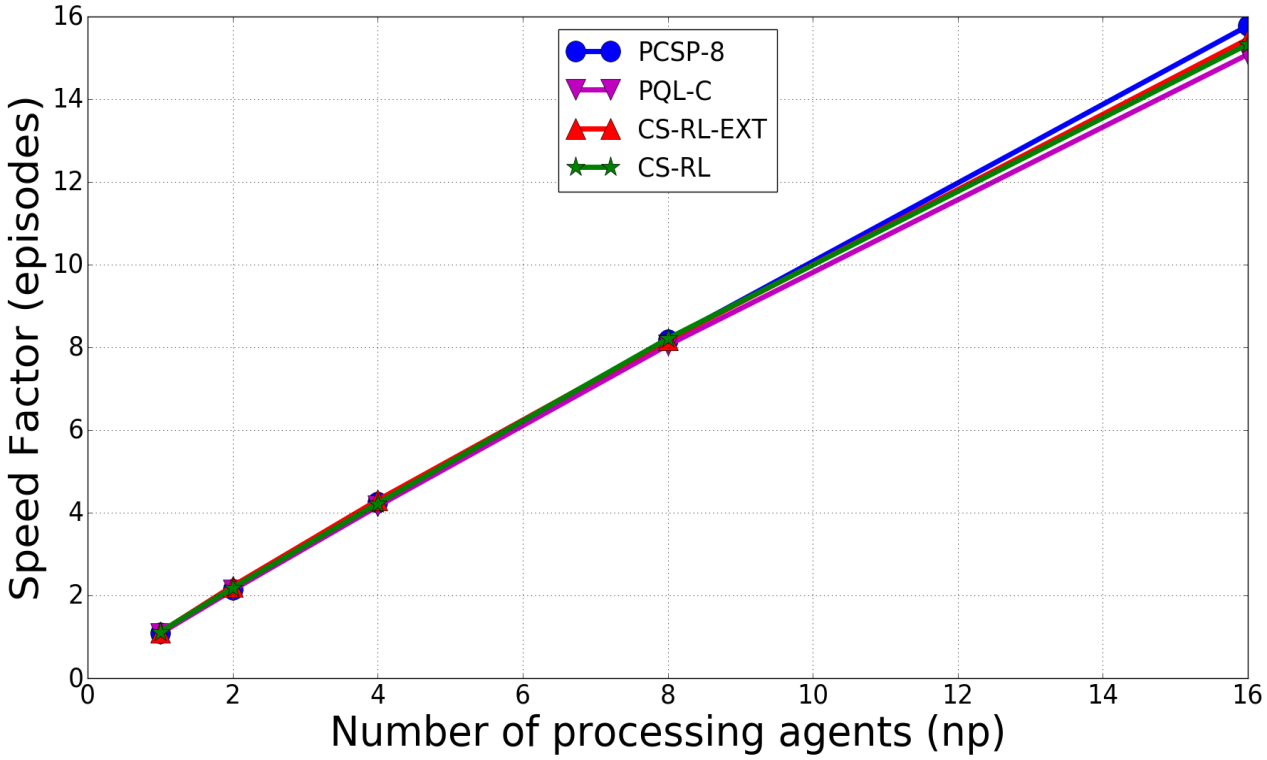
The single-agent Q-learning algorithm (SQL)

A naive implementation of the Constant Share RL (CS-RL) algorithm

An extended version of the CS-RL with local cache on the processing agents (CS-RL-EXT)

The PQL algorithm via a communication scheme with local cache (PQL-C).

PCSP REDUCE THE NUMBER OF EPISODES IN SAME RATE AS PQL WITH CENTRAL QT



Speed factor with respect to number of episodes of a SAQ execution

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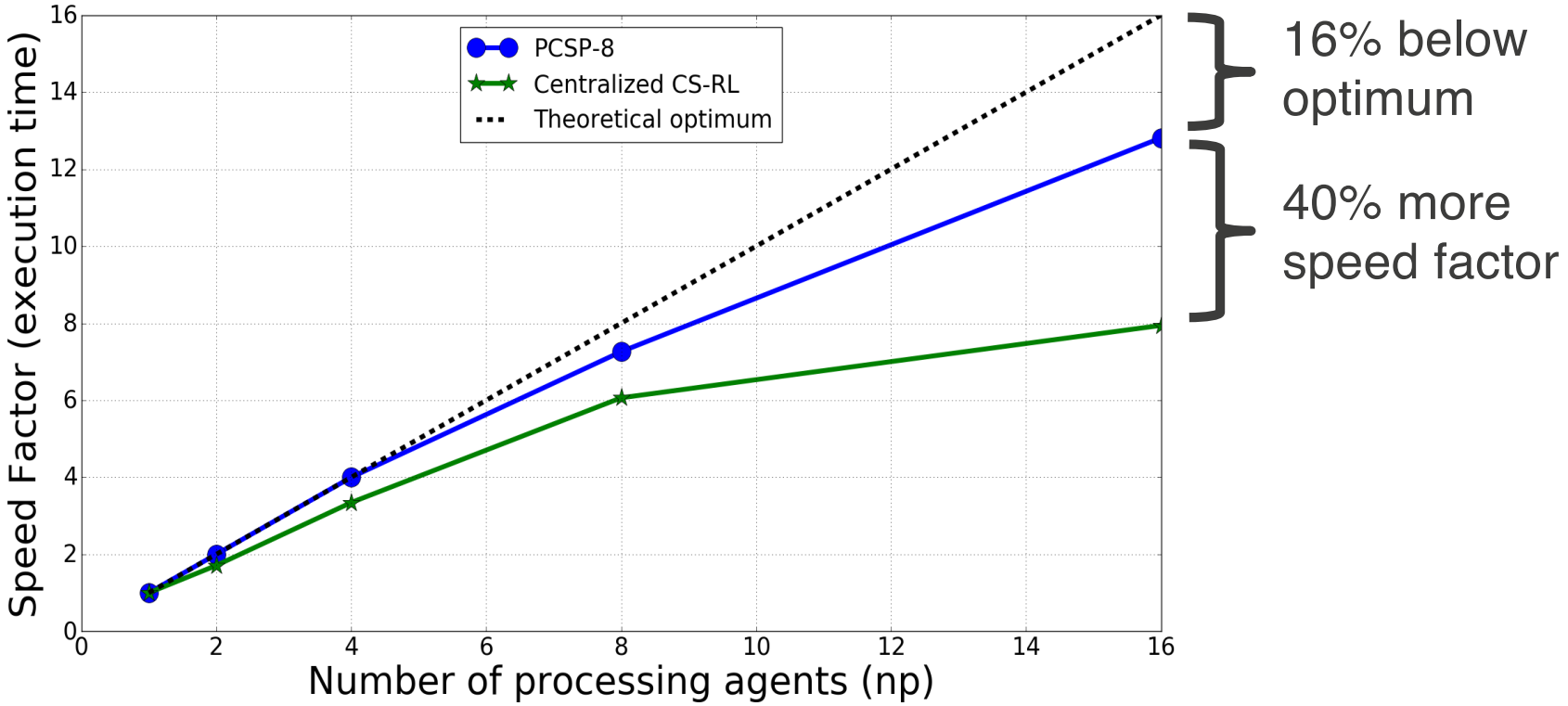
PCSP SCALES BETTER THAN CENTRALIZED PQL



Speed factor with respect to the execution time of the same algorithm with only one agent

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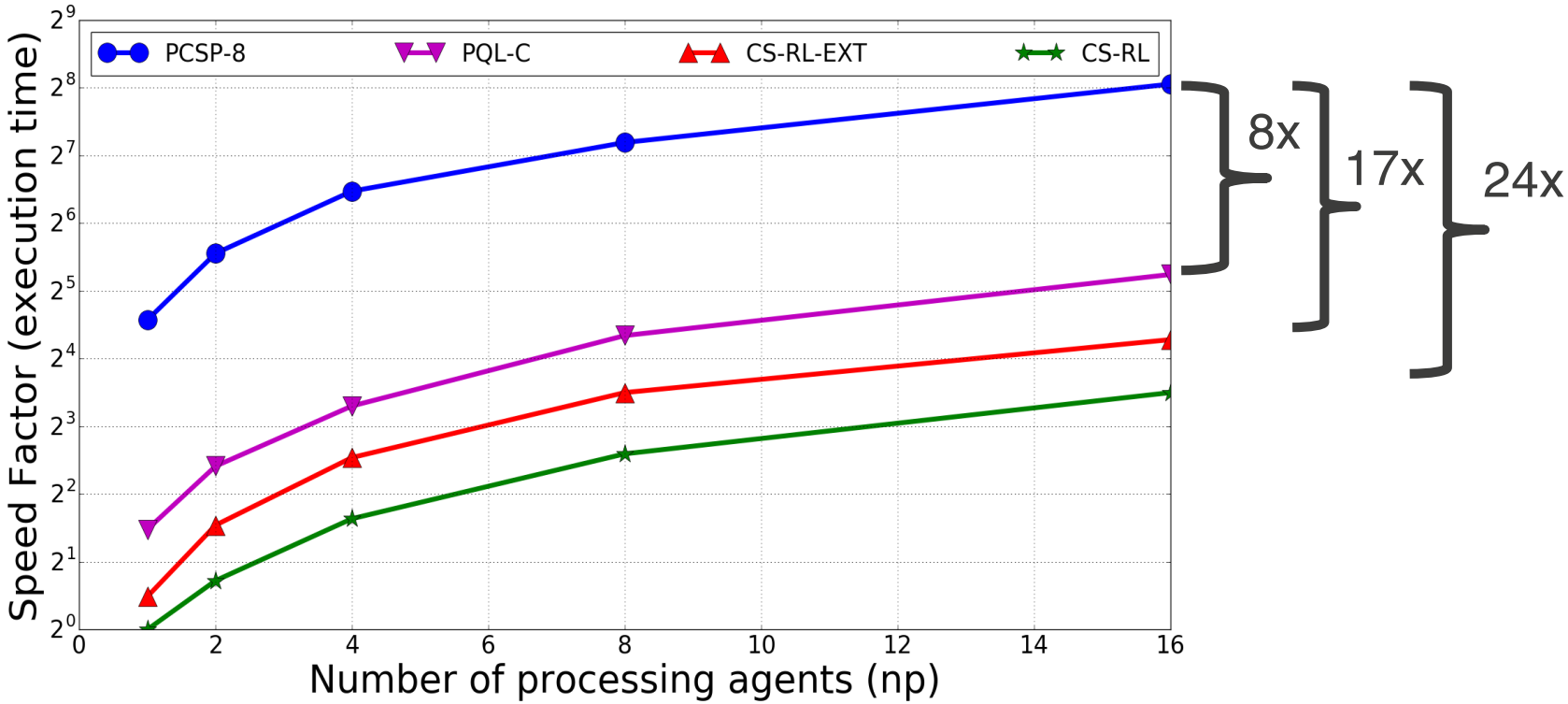
PCSP OVERCOMES ALL THE EVALUATED ALGORITHMS IN TERMS OF EXECUTION TIME



Speed factor with respect to the execution time of CS-RL with one StA and one PrA

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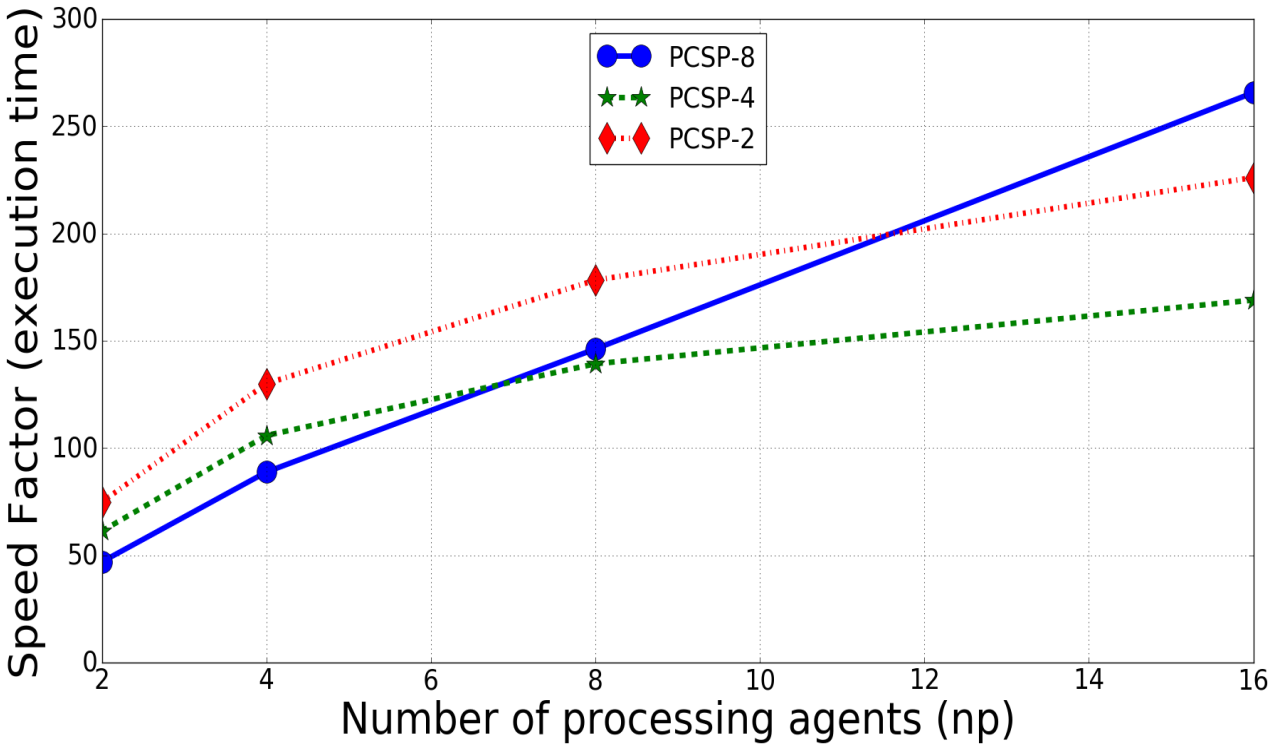
INCREASING BOTH n_p AND n_s SIMULTANEARLY ALLOWS A BETTER PERFORMANCE OF PCSP



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- ✓ PQL with co-allocation of processing and data
- ✓ Performance evaluation

CONCLUSIONS

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SUMMARY

Based on a flexible MA framework for developing efficient C-MAQL and PQL algorithms

PSCP minimizes the communication cost by combining a table partition strategy with a co-allocation of both processing and storage

PCSP can be deployed in both high performance (e.g. cloud data centers) and resource constrained devices (edge or fog computing devices)

FUTURE WORK: IMPROVE TABLE PARTITION AND ALLOCATION OF AGENTS

Design and implement partition algorithms that do not require any previous domain knowledge

Define new schemes for co-allocating agents different to pure load balancing of StA such as processing load, communication cost, etc.

Implement and evaluate the performance of other table-based RL algorithms.

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