△▽
:-dyna.

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and Jason Eisner

Dyna:

Toward a Self-Optimizing Declarative Language for Machine Learning Applications

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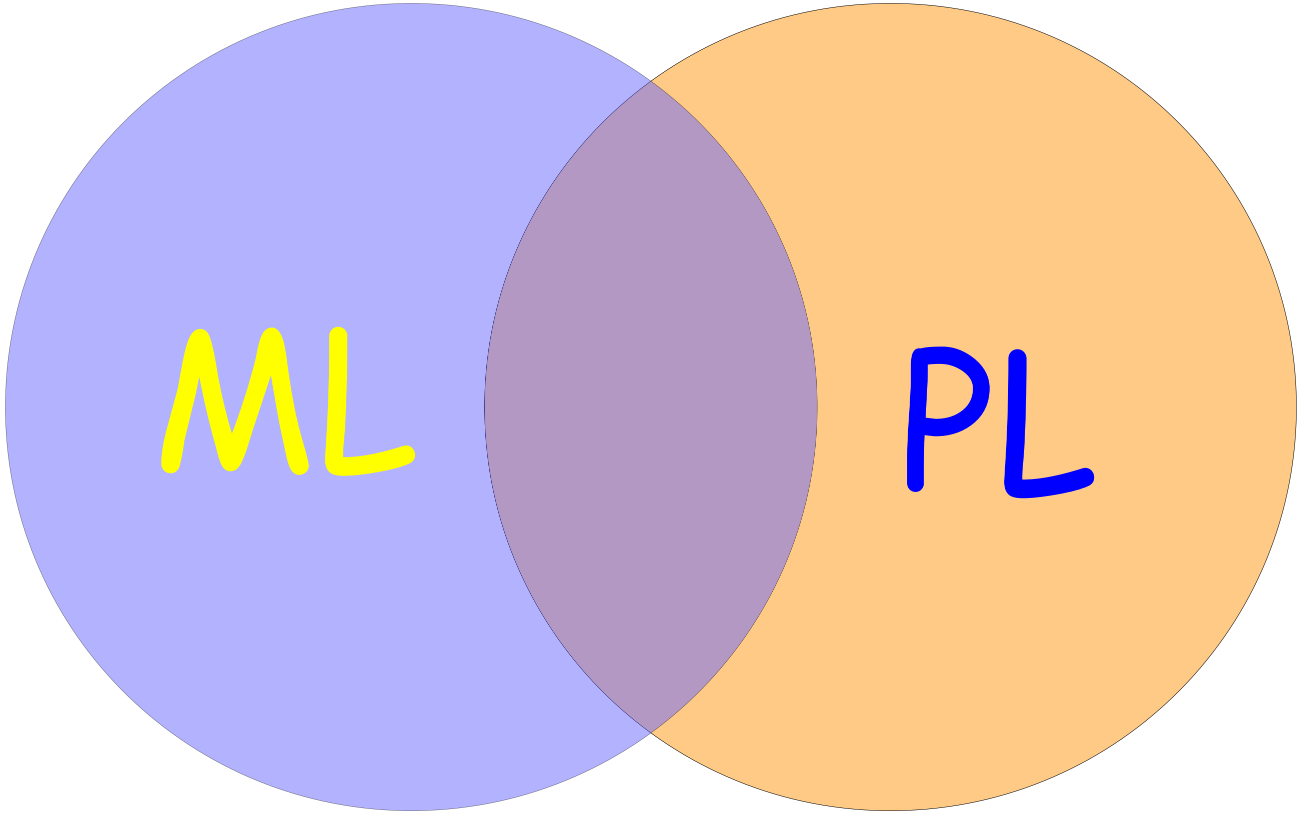

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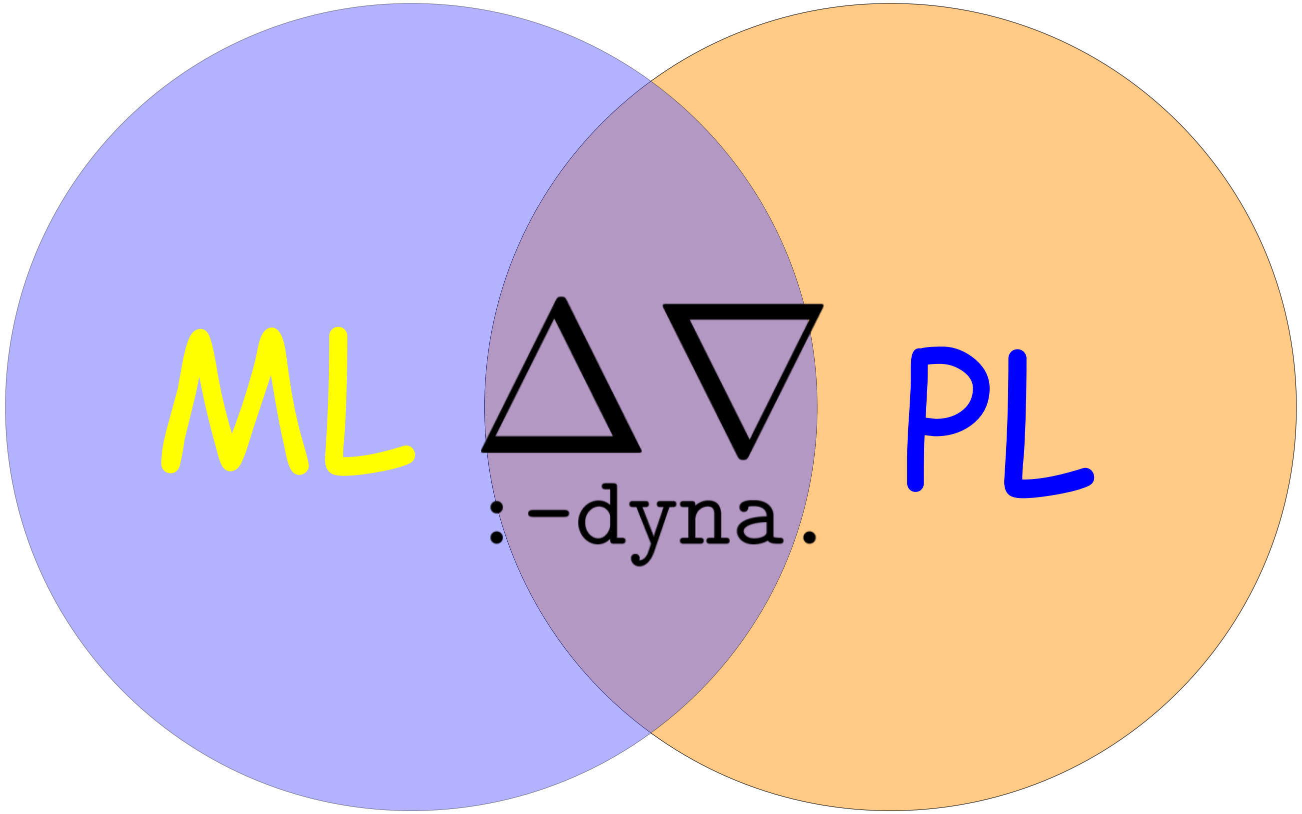

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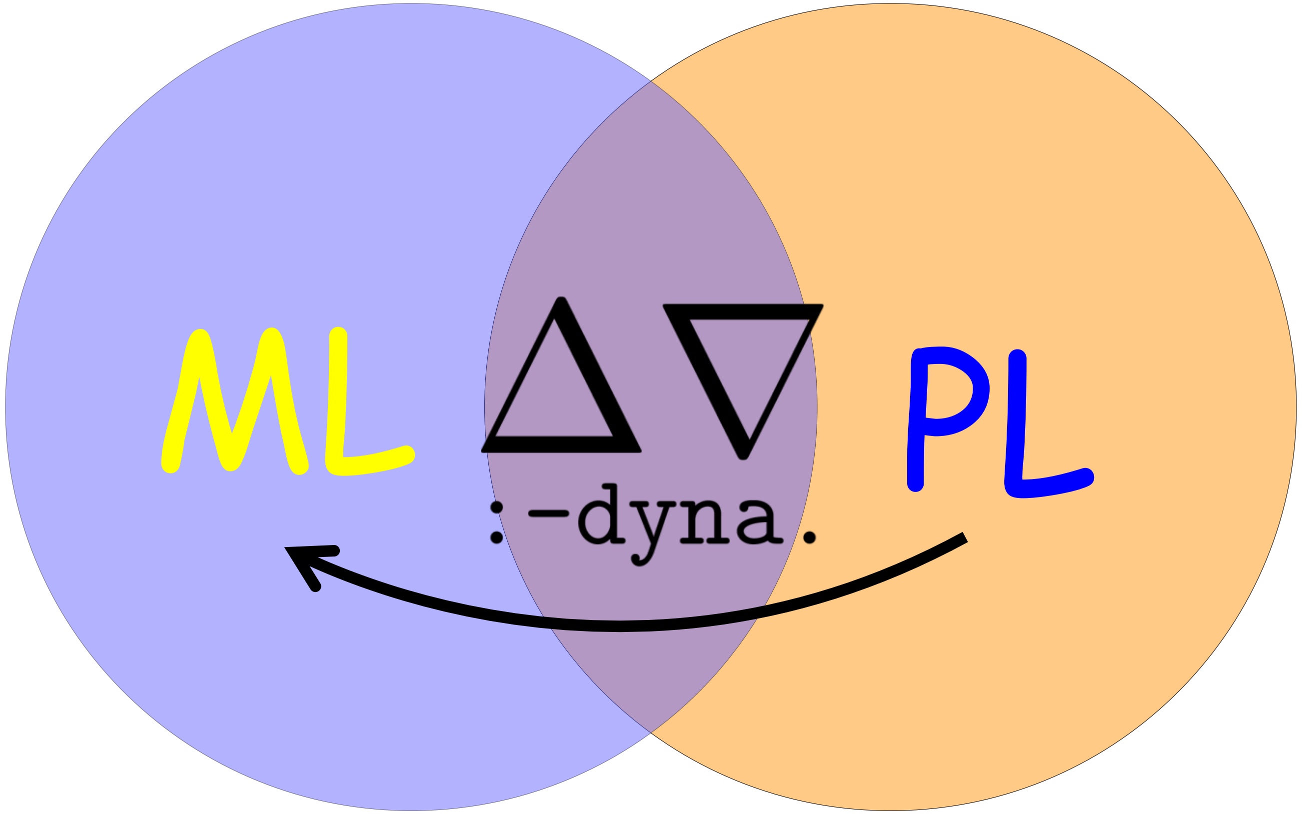

Faster to implement

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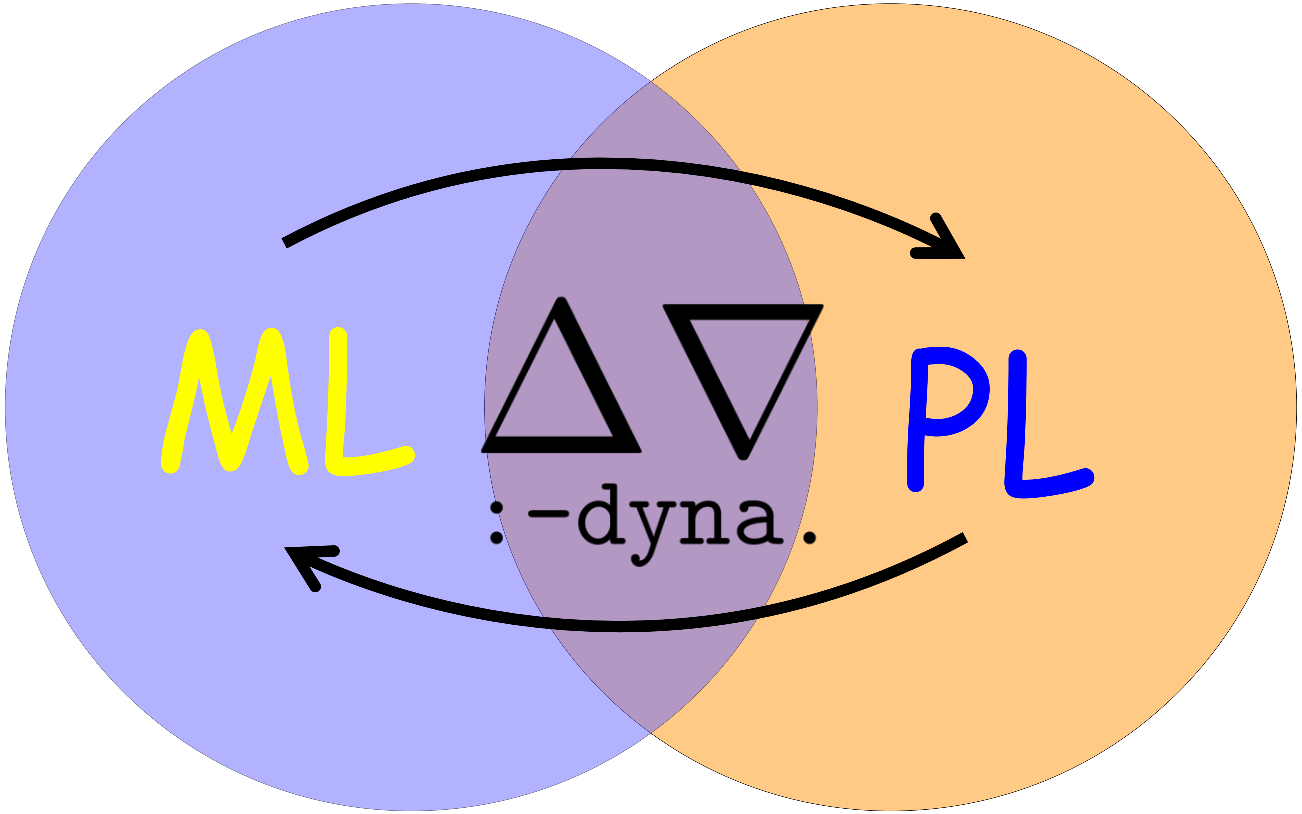
Faster execution



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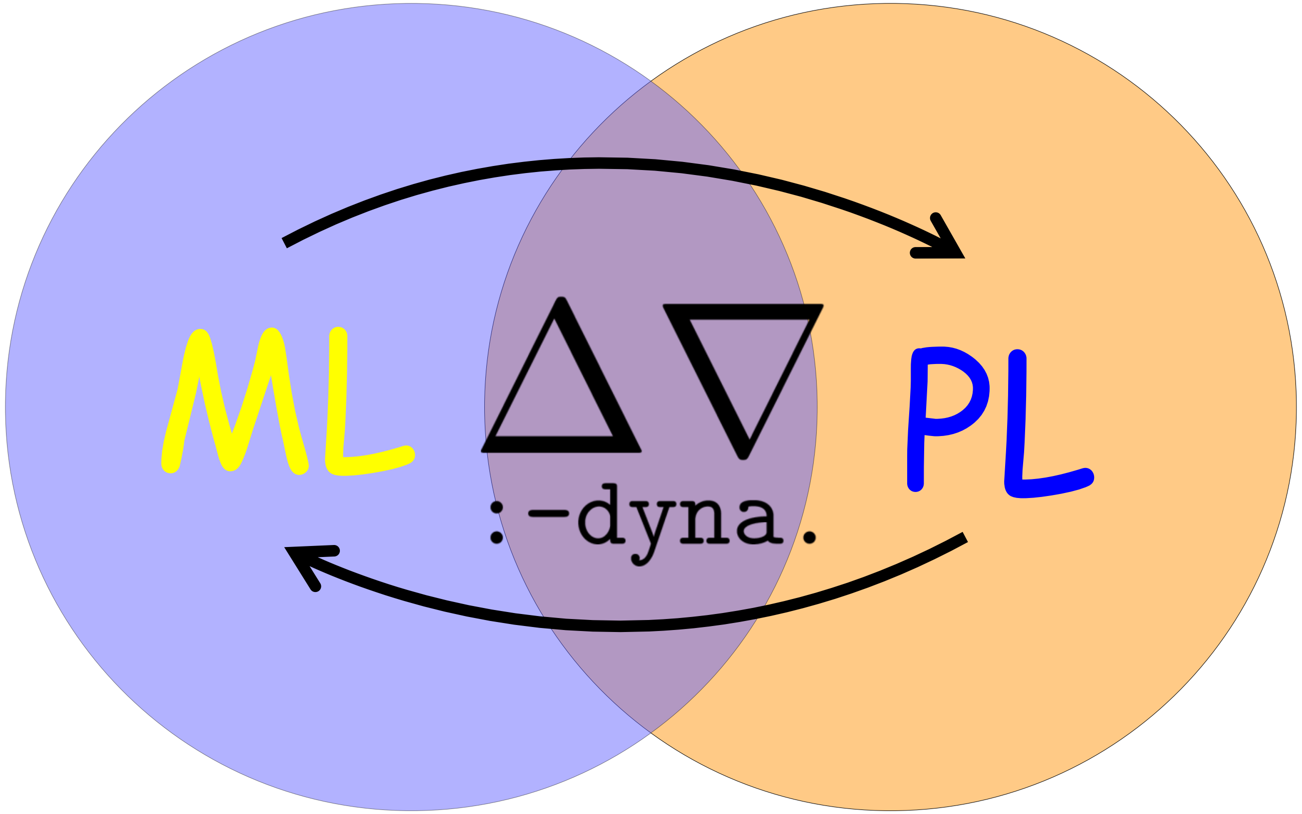

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Outline

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- Why Declarative Programming?

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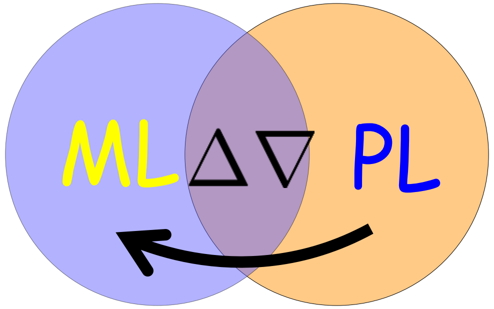
- Quick introduction to the Dyna language



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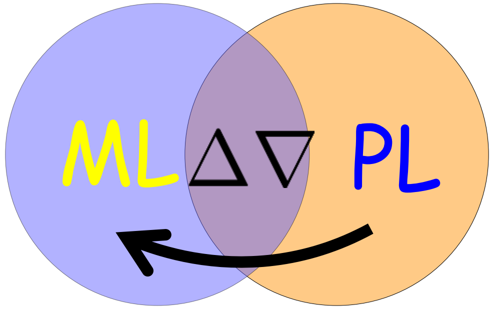
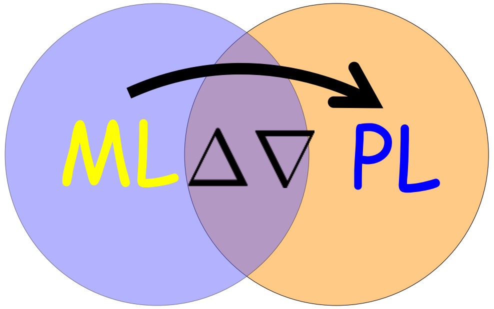


- Automatic optimization of Dyna programs



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- Solver seeks an efficient strategy (e.g., SQL query planning)

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    - Programmers usually only implement one
- Researchers don't have time to optimize the efficiency of their code
    - We can do better with automatic optimization

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  - Concurrency
- Difficult to reliably discover long range interactions in a program

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- Declarative language
- Based on weighted logic programming
- Prolog / Datalog like syntax
  - Uses pattern matching to define computation graphs
- Reactive
- Dyna programs are close to their mathematical description
  - Similar to functional programs

Dyna Day 1

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~~`c += z(foo(bar,5)).`~~

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Unlike Prolog:
Terms can have values
Terms are evaluated in place
Not just backtracking!

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edge("a", "b") = 10.
edge("b", "c") = 2.
edge("c", "d") = 7.
edge("d", "b") = 1.
start = "a".
end = "d".
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$$\mathrm{distance}(x) = \min_{y \in \mathrm{edges}(x,\cdot)} \mathrm{edge}(x, y) + \mathrm{distance}(y)$$

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Variables not present in the head of an expression are aggregated over like with the dot product example.

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Here the “`min=`“ aggregator only keeps the minimal value that we have computed

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Note: Aggregation was already present in our mathematical definition.

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? path_length
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Length at the end

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The distance of some other vertex

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All of the vertices

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? distance(X) > 7
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All the vertices more than 7 away

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```
? path_length
? distance("c")
? distance(X)
? distance(X) > 7
? edge("a",X)
```

All of the edges leaving "a"

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  - b **+=** a(X). % number
  - c **max=** a(X).
  - q **|=** p(X). % boolean
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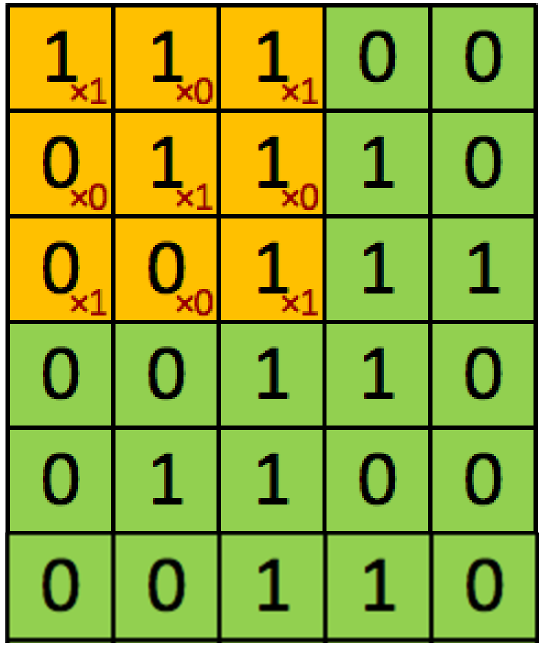
  - (Just define all of the operation of an commutative semigroup)

Neural Convolutional Layer



1 ×1	1 ×0	1 ×1	0	0
0 ×0	1 ×1	1 ×0	1	0
0 ×1	0 ×0	1 ×1	1	1
0	0	1	1	0
0	1	1	0	0
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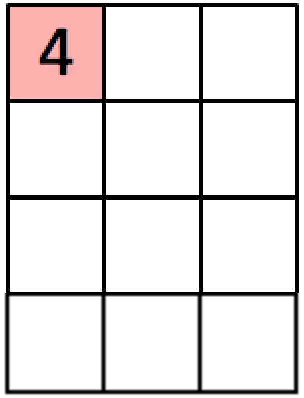
Input image



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Convolution output

http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

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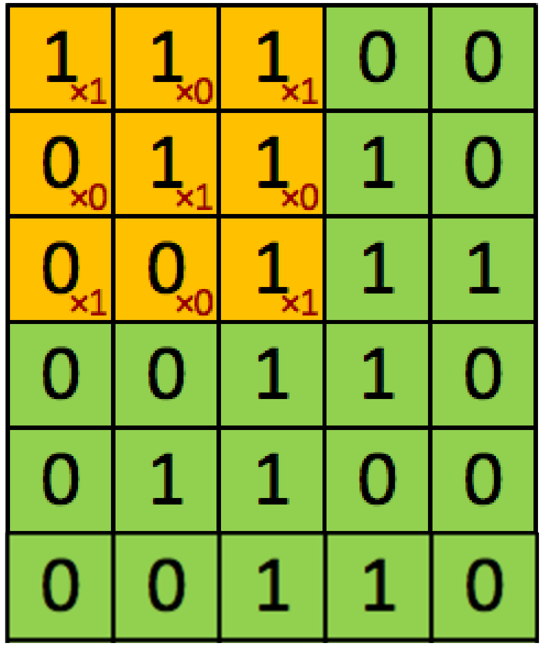

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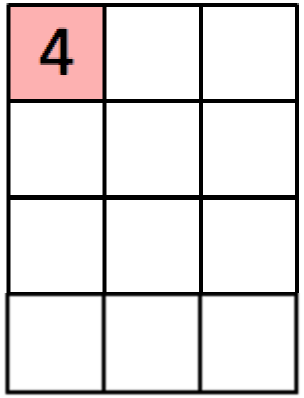

4		

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$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

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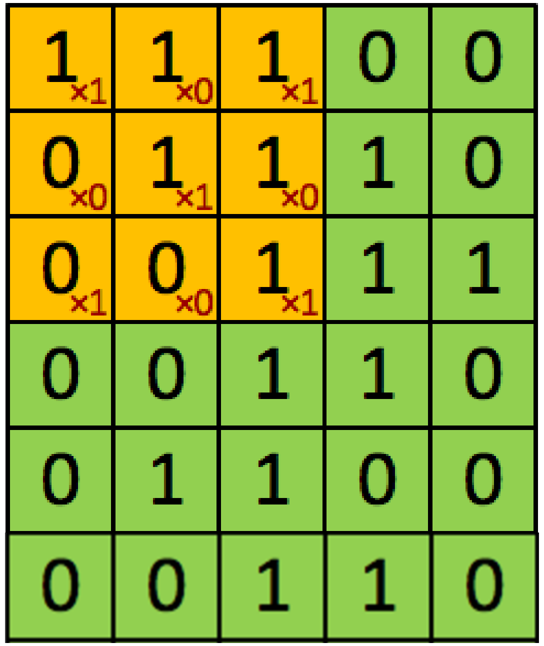

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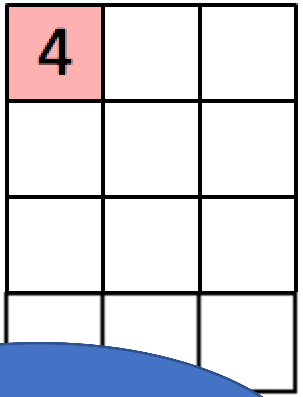

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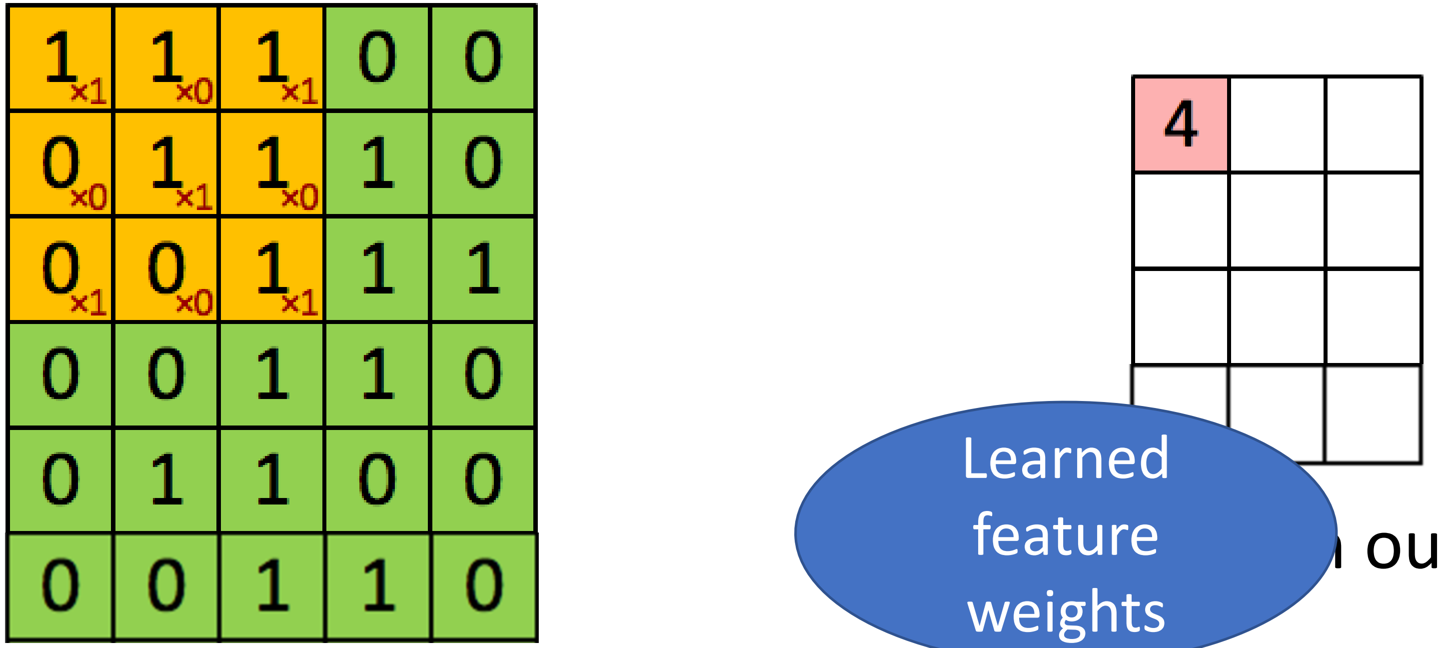

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Input image

4		

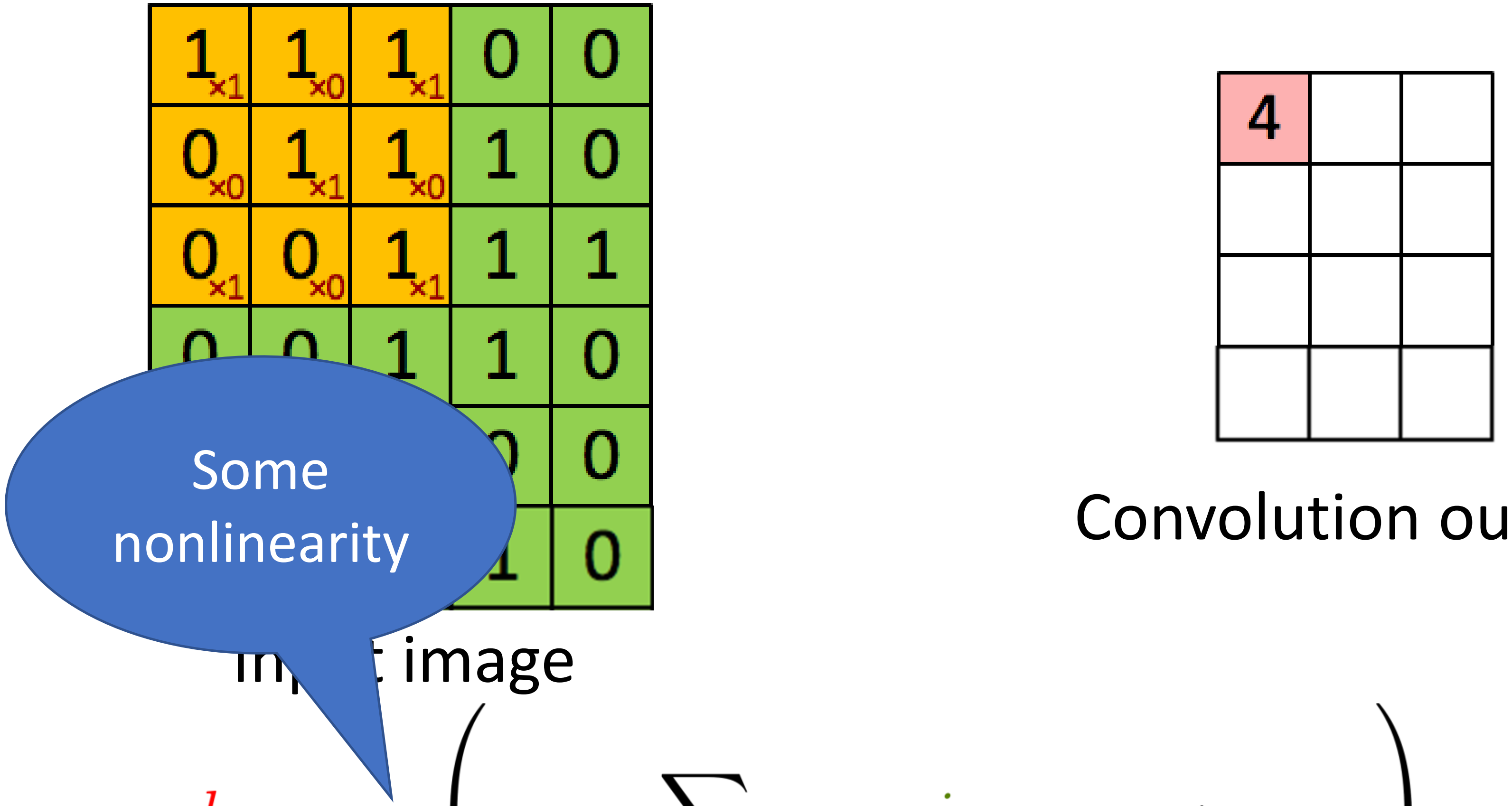
output

Learned feature weights

$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

Neural Convolutional Layer



In t image

Convolution output

$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

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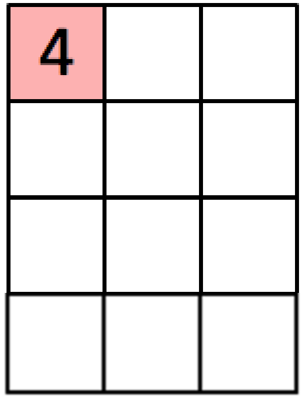
Neural Convolutional Layer

$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
[illegible]	1	1	0	0
[illegible]	0	1	1	0

Input image



4		

Convolution output

Convolution output

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Neural Convolutional layer

$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

```
          (activation(I, J)).
(X) := 1 / (1 + exp(-X)).
```

Neural Convolutional layer

$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

```
          σσ(X) := 1 / (1 + exp(-X)).
= σ(activation(I, J)).
activation(I, J) += input(I + M, J + N) * weight(M, N).
   weight(DX,DY) := random(*,-1,1) for DX:-1..1, DY:-1..1.
```

Neural Convolutional layer

$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

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= σ(activation(I, J))
activation(I, J) += input(I + M, J + N) * weight(M, N).
   weight(DX,DY) := random(-1,1) for DX:-1..1, DY:-1..1.
```

Summation became an aggregator

Neural Convolutional layer

$$h_{i,} \quad \Bigg(\quad {}_{m+i,n+j} * w_{m,n} \Bigg)$$

We can easily define rules over $\mathbb{R} \to \mathbb{R}$

```
          σσ(X) :=    / (1 + exp(-X)).
= σ(activation(I,  J)).
activation(I, J) += input(I + M, J + N) * weight(M, N).
   weight(DX,DY) := random(*,-1,1) for DX:-1..1, DY:-1..1.
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Neural Convolutional layer

$$h_{i,j} = \sigma\left(\sum_{m\in[-1,1],n\in[-1,1]} i_{m+i,n+j} * w_{m,n}\right)$$

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```

Our ranges over m and n are reflected in the shape of weight

Neural Convolutional layer

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```
          σσ(X) := 1 / (1 + exp(-X)).
= σ(activation(I, J)).
activation(I, J) := input(I + M, J + N) * weight(M, N).
   weight(DX,DY) := (*  ..1, DY:-1..1.
```

Here keys are integers but we can also support more complicated structures

More Neural

```
σ(X) = 1 / (1 + exp(-X)).
out(J) = σ(activation(J)).
activation(J) += out(I) * edge(I,J).
```

More Neural

```
σ(X) = 1 / (1 + exp(-X)).
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```

All weights have been
rolled into the edges
connecting neurons

More Neural

```
σ(X) = 1 / (1 + exp(-X)).
out(J) = σ(activation(J)).
activation(J) += out(I) * edge(I,J).
```

The output of a neuron is our nonlinearity applied to the sum of its inputs

More Neural

```
σ(X) = 1 / (1 + exp(-X)).
out(J) = σ(activation(J)).
activation(J) += out(I) * edge(I,J).
```

Note: nowhere in this program do we specify the form of our variables `I, J`

More Neural

```
σ(X) = 1 / (1 + exp(-X)).
out(J) = σ(activation(J)).
activation(J) += out(I) * edge(I,J).
```

Instead we can specify the structure of keys inside the definition of edge.

```
edge(input(X,Y),hidden(X+DX,Y+DY)) = weight(DX,DY).
weight(DX,DY) := random(*,-1,1) for DX:-1..1, DY:-1..1.
```

More Neural

```
σ(X) = 1 / (1 + exp(-X)).
out(J) = σ(activation(J)).
activation(J) += out(I) * edge(I,J).
```

```
edge(input(X,Y),hidden(X+DX,Y+DY)) = weight(DX,DY).
weight(DX,DY) := random(*,-1,1) for DX:-1..1, DY -1..1.
```

The weight do not depend on the absolute location of the input, so this is a convolution again.

Dyna Makes Algorithms Easy

Dyna Makes Algorithms Easy

- Gibbs, MCMC – flip variable, compute likelihood ratio, accept or reject

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- Neural networks – computation graphs passing dense matrices

Dyna Makes Algorithms Easy

- Gibbs, MCMC – flip variable, compute likelihood ratio, accept or reject
- Iterative algorithms – loopy belief propagation, numerical optimization
- Neural networks – computation graphs passing dense matrices
- Branch-and-bound, Davis–Putnam–Logemann–Loveland (DPLL)

Dyna Makes Algorithms Easy

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All use graphs to propagate changes

Dyna Makes Algorithms Easy

- Gibbs, MCMC – flip variable, compute likeliho … or reject
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  optimization
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All use graphs to propagate changes

- Implementations and more in:
  - Dyna: Extending Datalog for modern AI. (Eisner & Filardo 2011)
  - Dyna: A non-probabilistic language for probabilistic AI. (Eisner 2009)

How much can a declarative language save us?

Implementing shortest path

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
               + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
              + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Java (Procedural)

```
queue = new FifoQueue<Pair<String, Float>>();
distances = new HashMap<String, Float>();
edges = new HashMap<Pair<String, String>,Float>();
// load edges
queue.push("start");
while(!queue.empty()) {
  d = queue.pop();
  for(e : edge) {
    if(e.first().second().equals(d.first())) {
      if(distance.get(e.first()) <
         d.second() + e.second()) {
        distance.put(e.first(),
                     d.second() + e.second());
        queue.push(e.first());
      }
    }
  }
}
path_length = distances.get("end");
```

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
               + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Java (Procedural)

```
queue = new PriorityQueue<String, Float>();
distances = new HashMap<String, Float>();
edges = new HashMap<Pair<String, String>,Float>();
// load edges
queue.push("start", 0);
while(!queue.empty()) {
  d = queue.pop();
  for(e : edge) {
    if(e.first().second().equals(d.first())) {
      n = d.second() + e.second();
      if(distance.get(e.first()) < n) {
        distance.put(e.first(), n);
        queue.push(e.first(), n);
      }
    }
  }
}
path_length = distances.get("end");
```

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
              + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Java (Procedural)

```
queue = new PriorityQueue<String, Float>();
distances = new HashMap<String, Float>();
edges = new HashMap<String,Map<String,Float>>();
// load edges
queue.push("start", 0);
while(!queue.empty()) {
  d = queue.pop();
  for(e : edge.get(d.first())) {
    n = d.second() + e.second();
    if(distance.get(e.first()) < n) {
      distance.put(e.first(), n);
      queue.push(e.first(), n);
    }
  }
}
path_length = distances.get("end");
```

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
              + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Java (Procedural)

```
placeIndex = new HashMap<String,Integer>();
queue = new PriorityQueue<Integer, Float>();
distances = new float[num_places];
edges = new float[num_places][num_places];
// load edges
queue.push(placesIndex.get("start"), 0);
while(!queue.empty()) {
  d = queue.pop();
  l = edges[d.first()];
  for(j = 0; j < l.length; j++) {
    n = d.second() + l[j];
    if(distances[j] < n) {
      distances[j] = n;
      queue.push(j, n);
    }
  }
}
path_length = distances[placeIndex.get("end")];
```

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
               + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Java (Procedural)

```
placeIndex = new HashMap<String,Integer>();
edges = new float[num_places][num_places];
// load edges
float distance(from) {
  if(from == placeIndex.get("start")) {
    return 0;
  }
  l = edges[from];
  r = infinity;
  for(j = 0; j < l.length; j++) {
    n = distance(j) + l[j];
    if(n < r)
      r = n;
  }
  return r;
}
path_length = distance(placeIndex.get("end"));
```

Implementing shortest path

Dyna (Declarative)

```
distance(X) min= edge(X, Y)
                 + distance(Y).
distance(start) min= 0.
path_length = distance(end).
```

Java (Procedural)

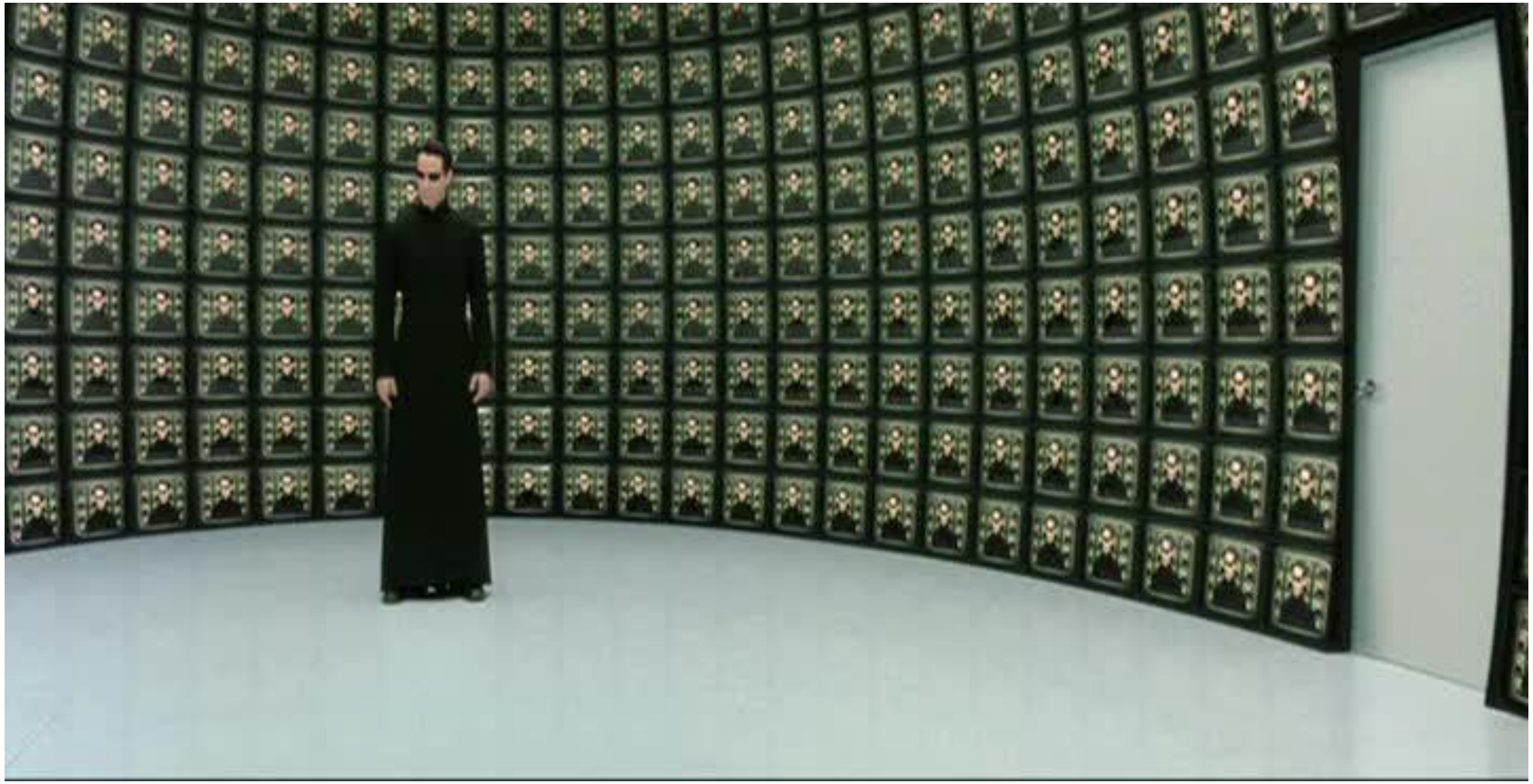
```
placeIndex = ne                            ();
edges = new
// load
float
  i
}
path_
```

A single Dyna program can represent hundreds of possible implementations.

Other implementations (not shown here) include A* and bidirectional search, and choice of data structures to support dynamic graphs

Given all of these implementations,

Given all of these implementations, the problem is choice



The Matrix Reloaded (2003)

If you are Neo, you have two choices

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- Take the Architect’s deal
    - Restart the Matrix
    - Let all the humans in Zion die
        - But restart Zion with 16 females and 7 males (fight another day)

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  - Already tried this <u>5 times</u>

If you are Neo, you have two choices

- Take the Architect’s deal
  - Restart the Matrix
  - Let all the humans in Zion die
    - But restart Zion with 16 females and 7 males (fight another day)
  - Already tried this 5 times
  - Current argmax

If you are Neo, you have two choices

- Take the Architect’s deal
    - Restart the Matrix
    - Let all the humans in Zion die
        - But restart Zion with 16 females and 7 males (fight another day)
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    - Current argmax
- Follow “an emotion specifically designed to overwhelm logic & reason”
    - Save Trinity

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- Take the Architect’s deal
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        - But restart Zion with 16 females and 7 males (fight another day)
    - Already tried this <u>5 times</u>
    - Current argmax
- Follow “an emotion specifically designed to overwhelm logic & reason”
    - Save Trinity
    - YOLO, figure this out as we go (unknown reward)

This raises the next question …

This raises the next question …

can machines love

This raises the next question …

can machines love

or at least make irrational choices

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$$action = \text{argmax } \pi(\cdot | \ldots)$$

The “Rational” Choice

This raises the next question …
can machines love
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$$action = \text{argmax}\ \pi(\cdot|\ldots)$$

The "Rational" Choice

$$action \sim \pi(\cdot|\ldots)$$

The "Irrational" Choice

(Randomly sample)

This raises the next question …

can machines love

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$$action = \text{argmax } \pi(\cdot|\ldots)$$

The “Rational” Choice

Exploitation

$$action \sim \pi(\cdot|\ldots)$$

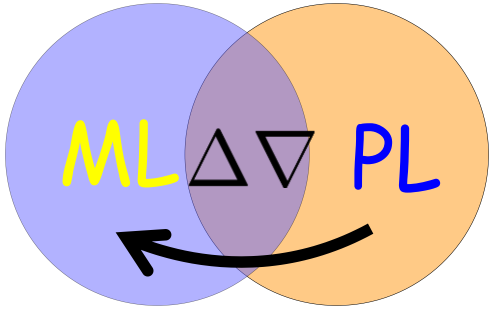
The “Irrational” Choice

(Randomly sample)

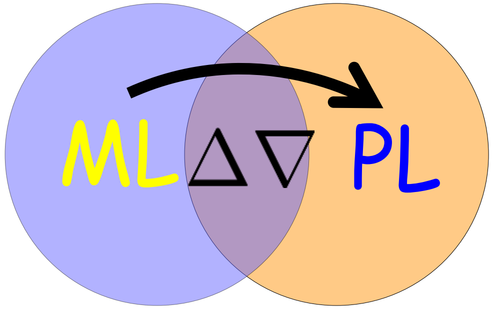
Exploration

Outline

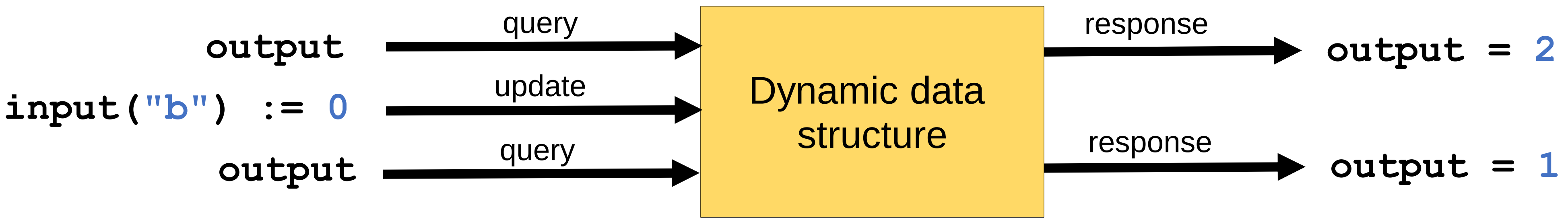
- Why Declarative Programming?
- Quick introduction to the Dyna language



- **Automatic optimization of Dyna programs**



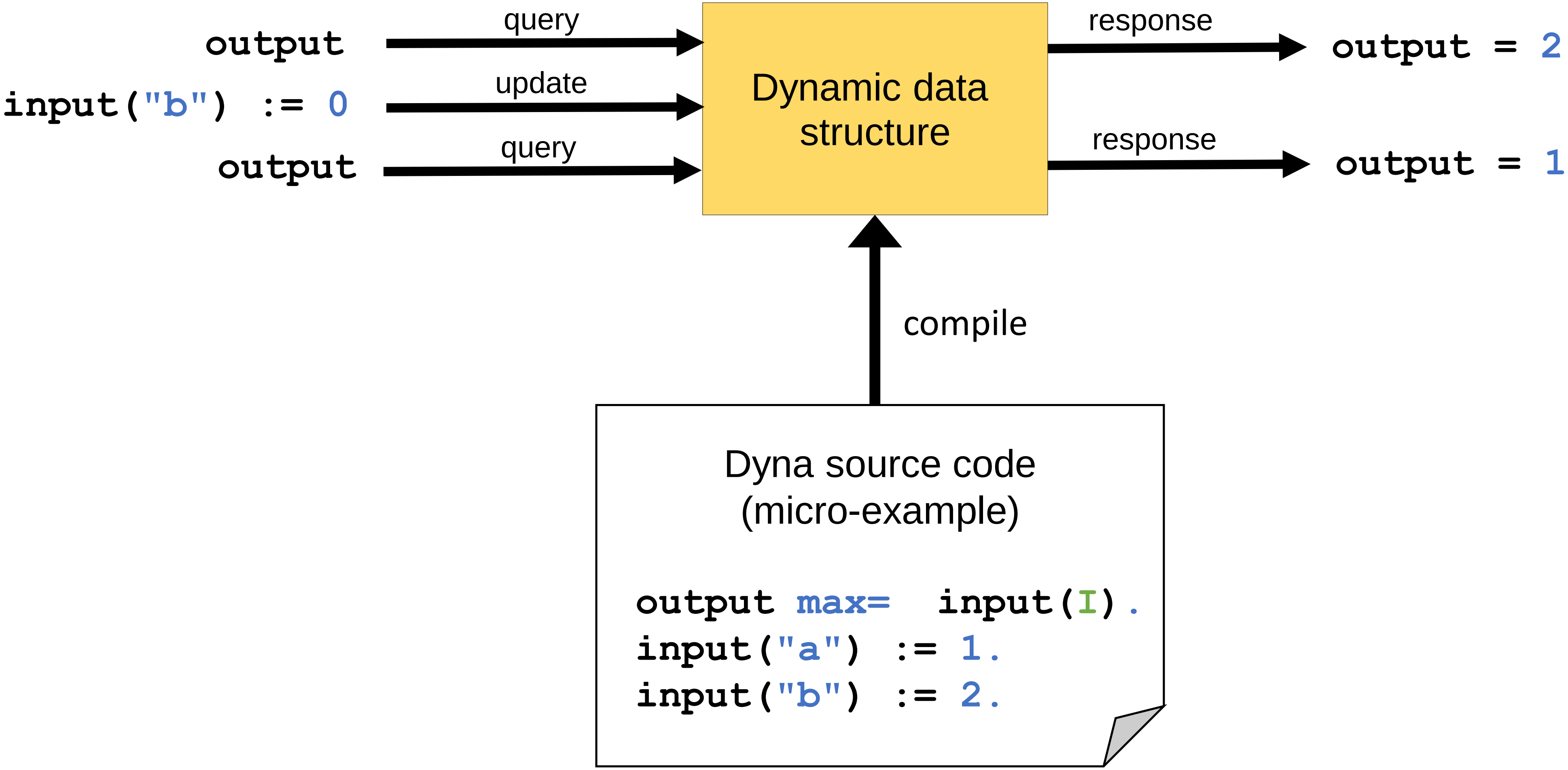
Dyna



Dyna source code
(micro-example)

```
output max=  input(I).
input("a") := 1.
input("b") := 2.
```

Dyna



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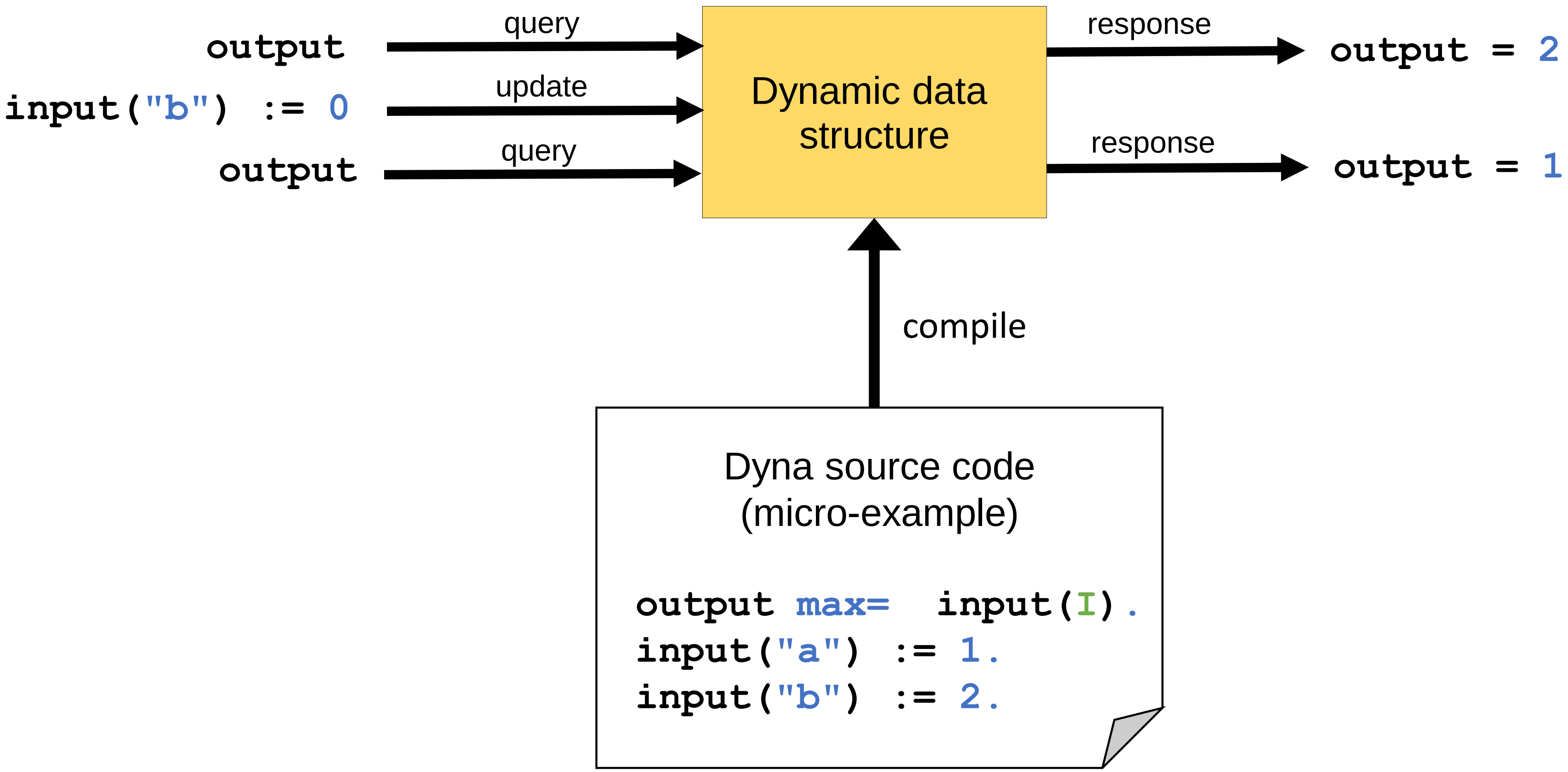

output

query

input("b") := 0

update

output

query

Dynamic data structure

response

output = 2

response

output = 1

compile

Dyna source code (micro-example)

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output max=  input(I).
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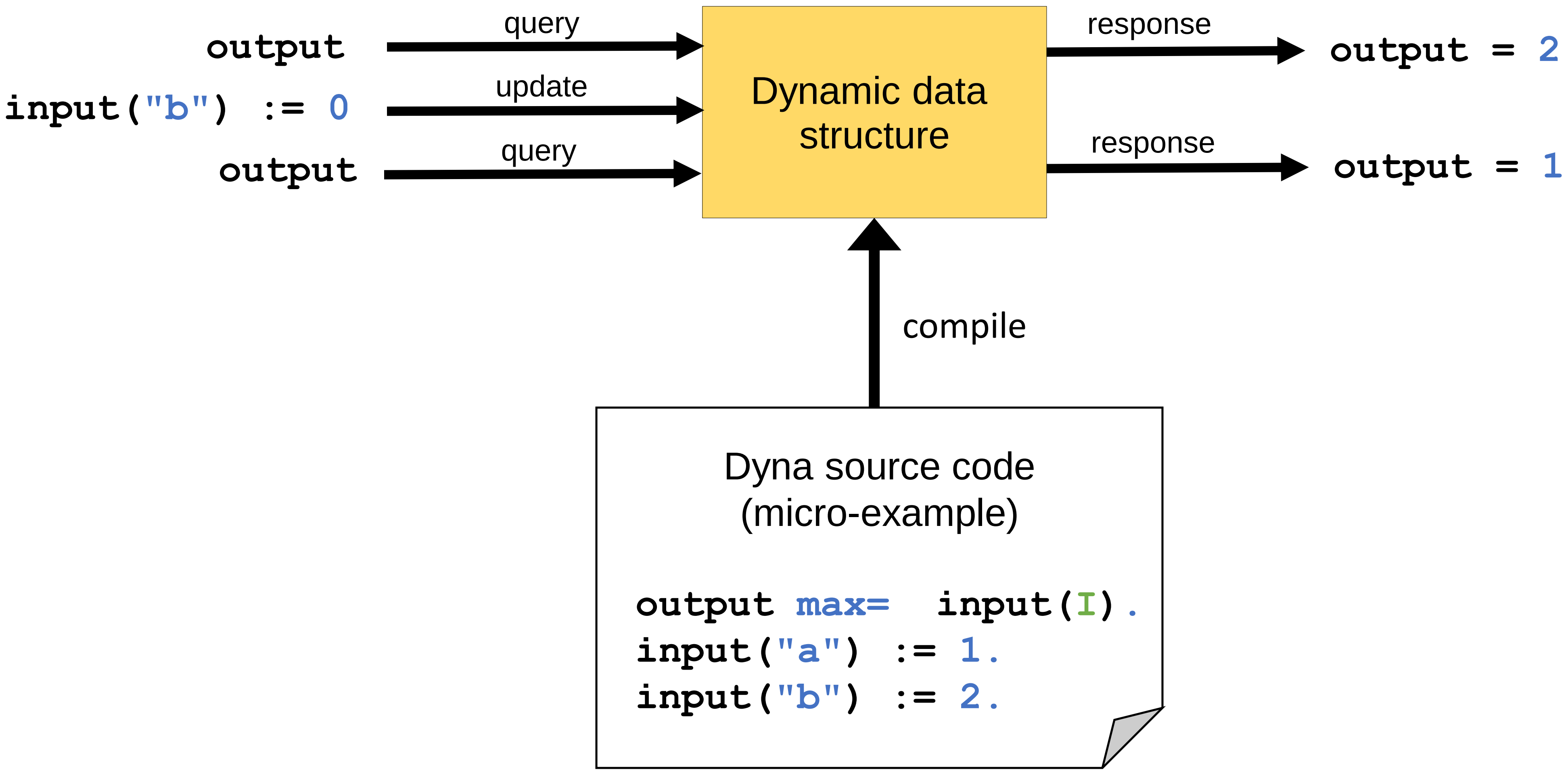

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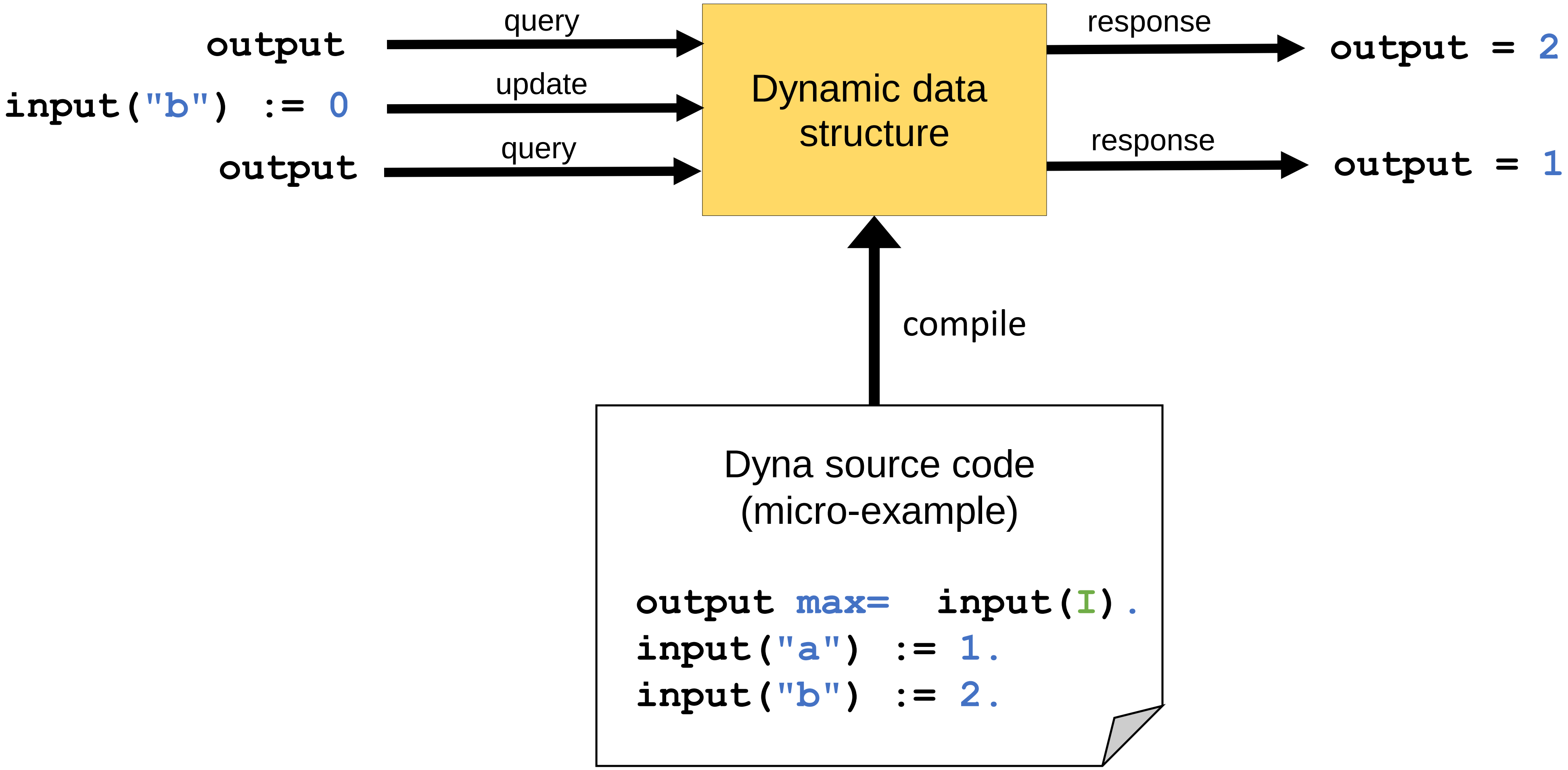

`output` query

`input("b") := 0` update

`output` query

Dynamic data structure

response `output = 2`

response `output = 1`

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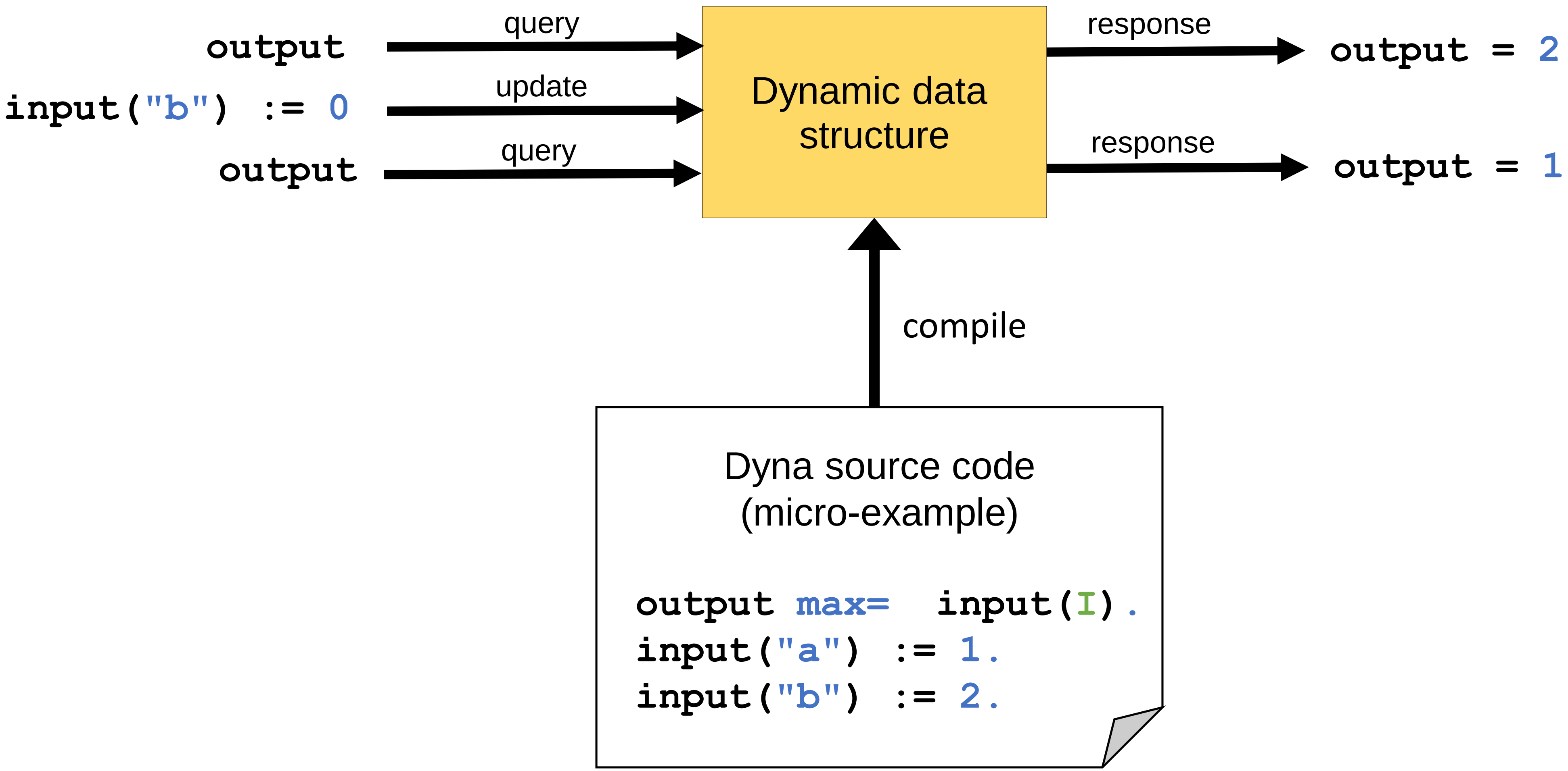

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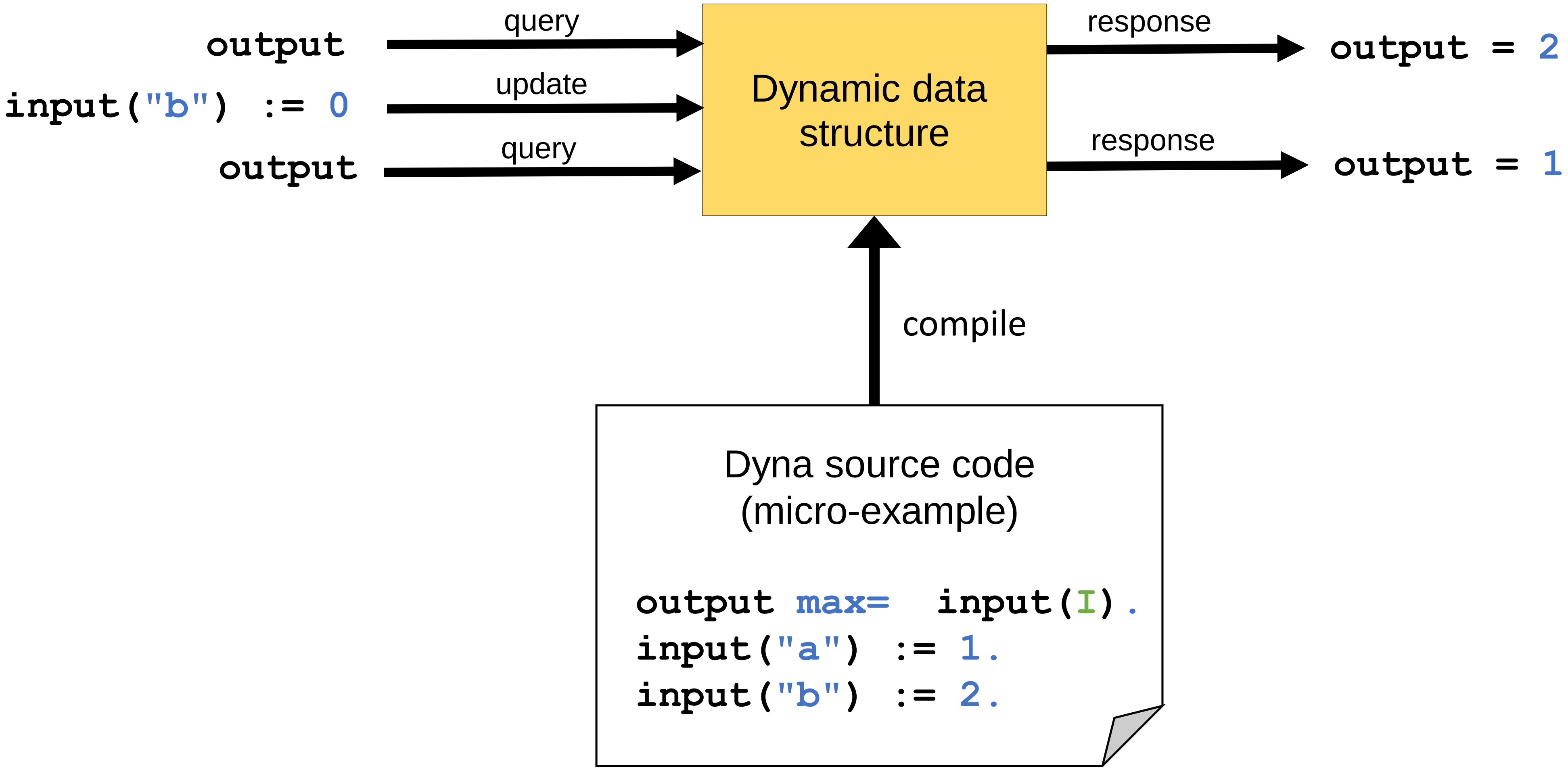

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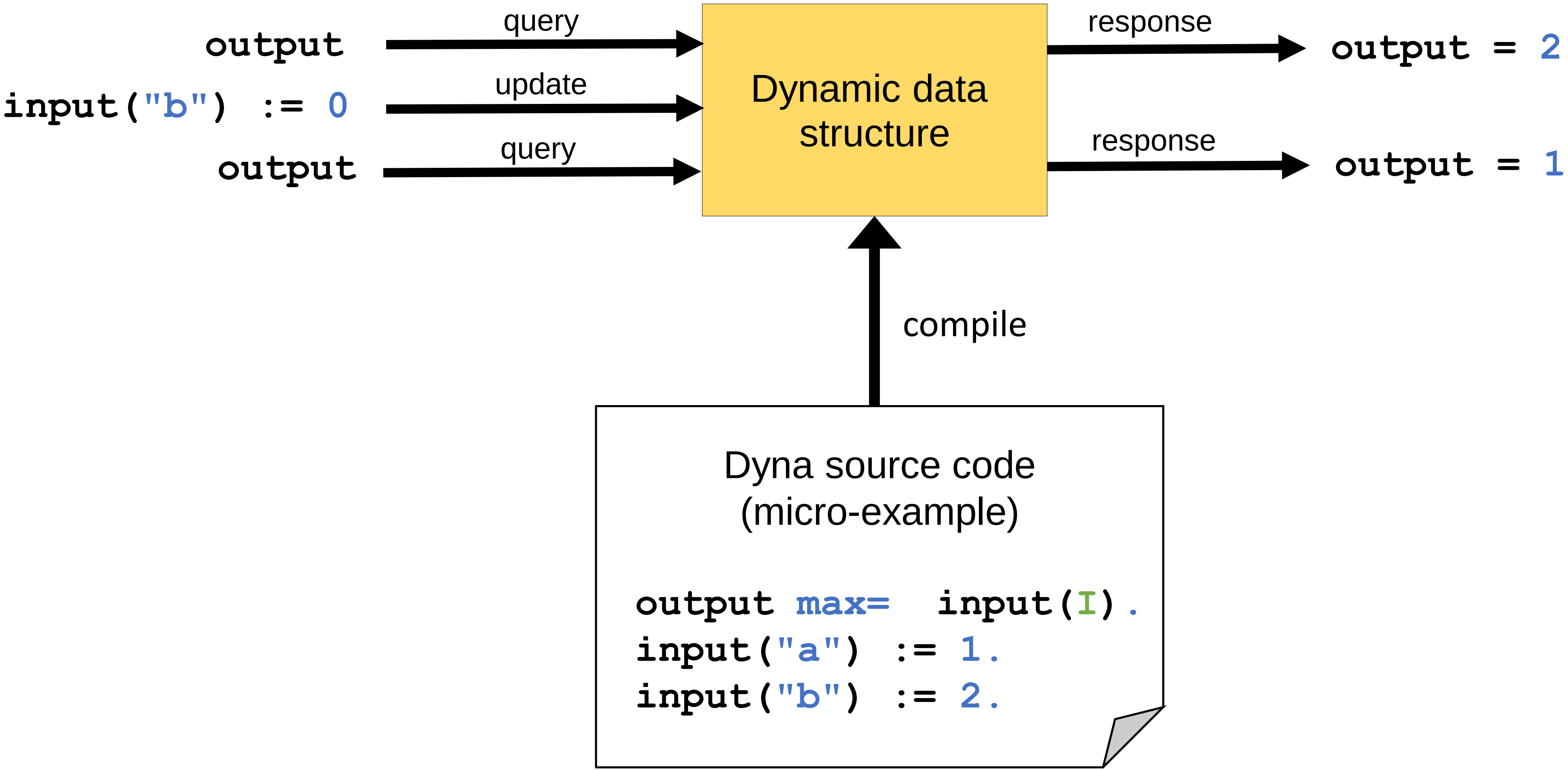

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response `output = 2`

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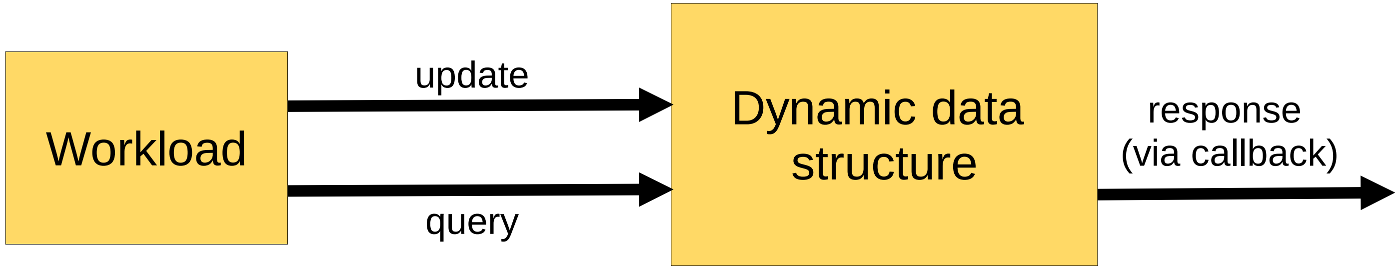
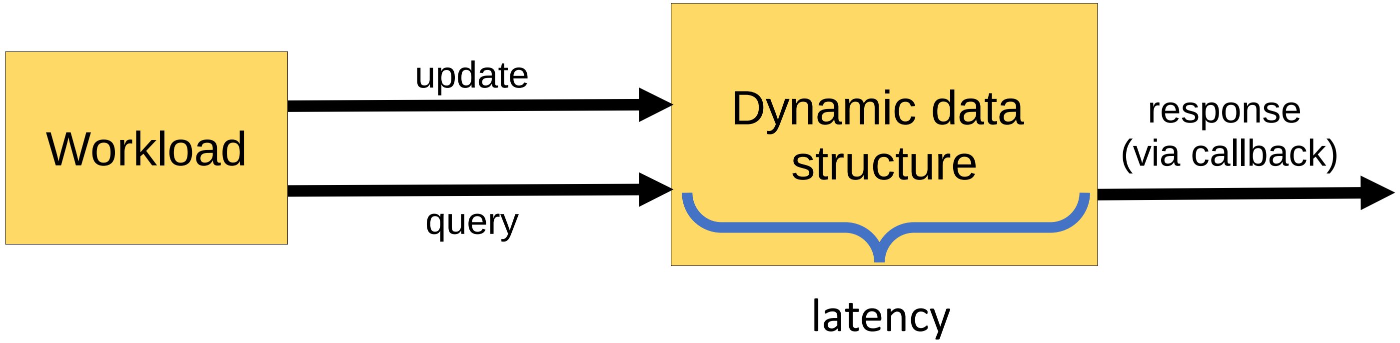
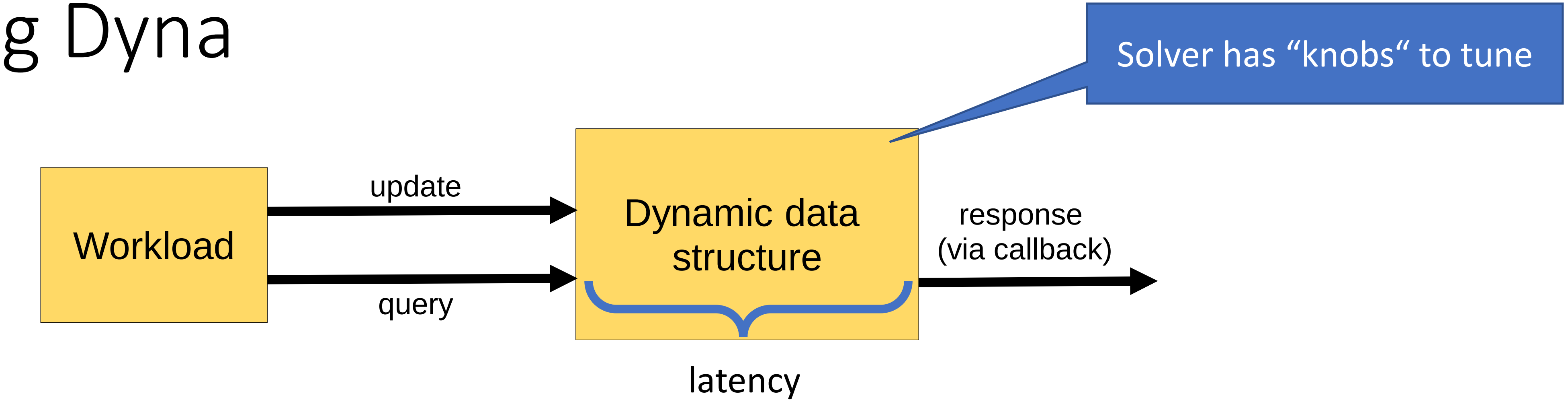
Tuning Dyna


Workload
update
query
Dynamic data structure
response (via callback)

Tuning Dyna


Workload
update
query
Dynamic data structure
response
(via callback)
latency

Tuning Dyna



Solver has “knobs“ to tune

Workload

update

query

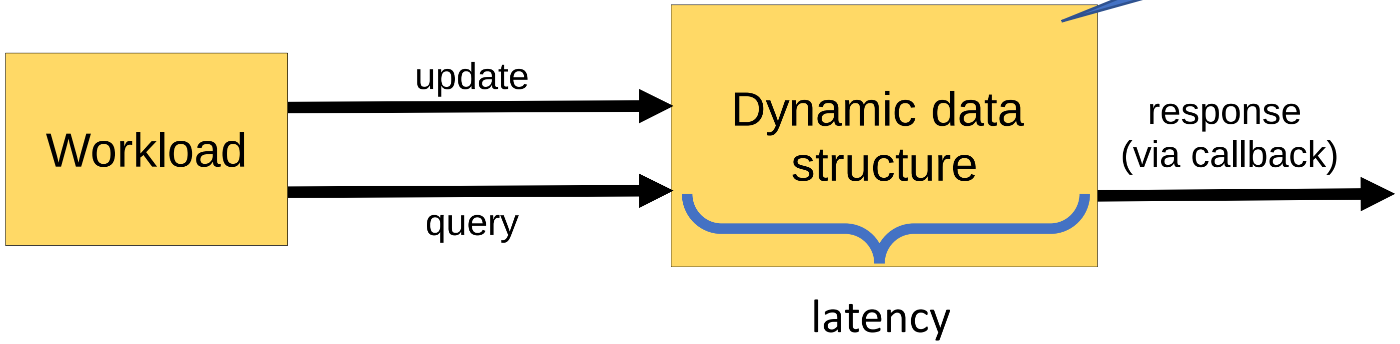
Dynamic data structure

response (via callback)

latency

Tuning Dyna

Solver has “knobs“ to tune



Workload

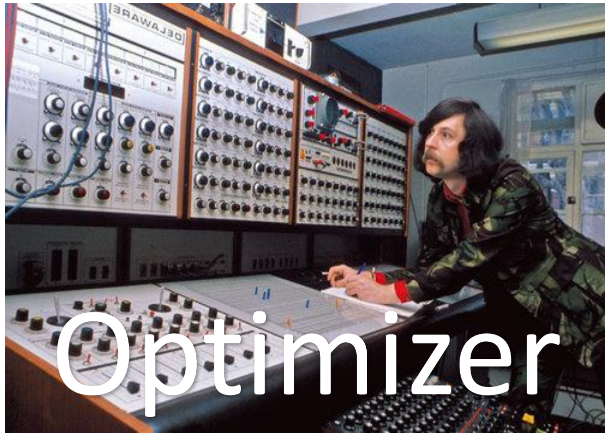
update

query

Dynamic data structure

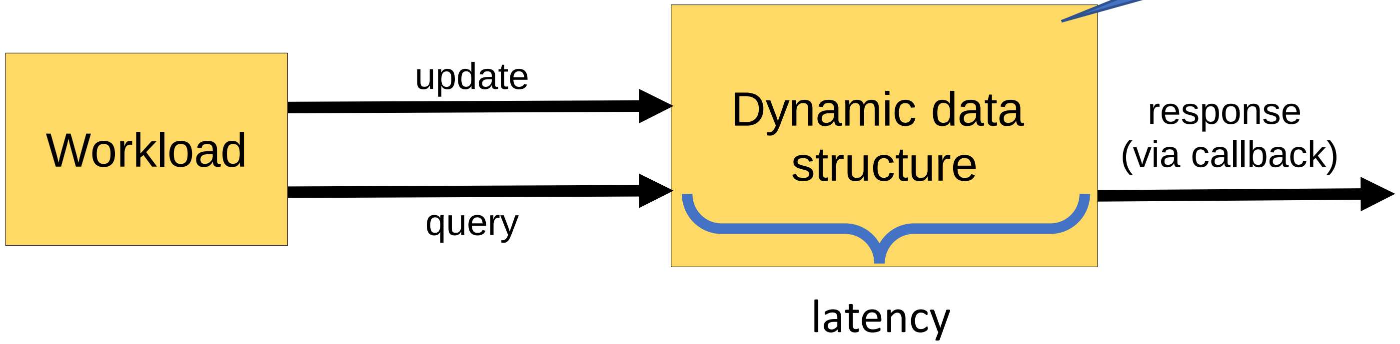
latency

response (via callback)



Tuning Dyna

Solver has “knobs“ to tune


Workload

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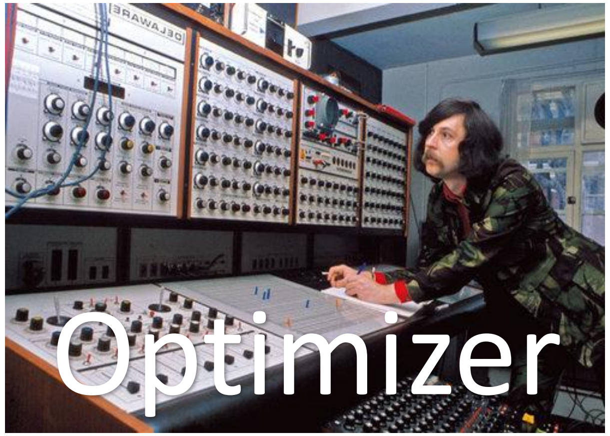
response (via callback)



Example knob: eager or lazy updates?
e.g., **dynamic max data structure**

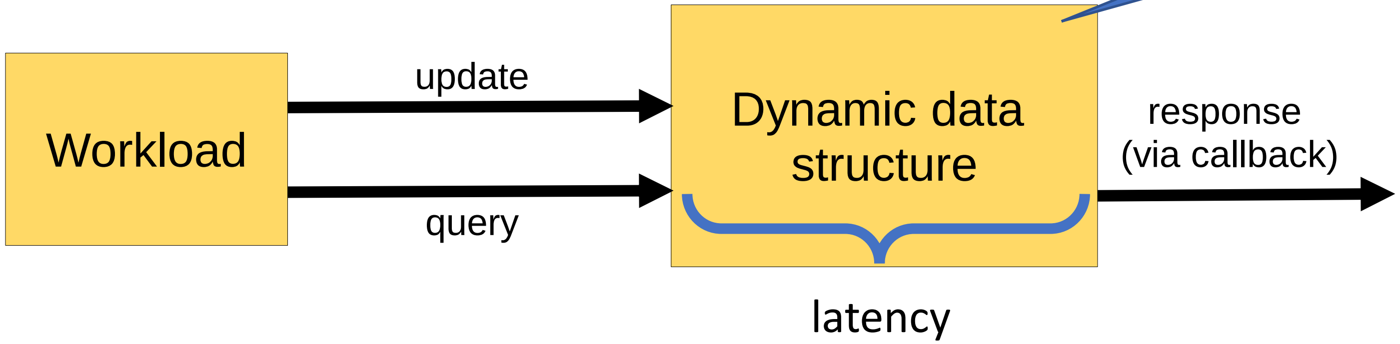
```
% Dyna:
output max= input(I).
```

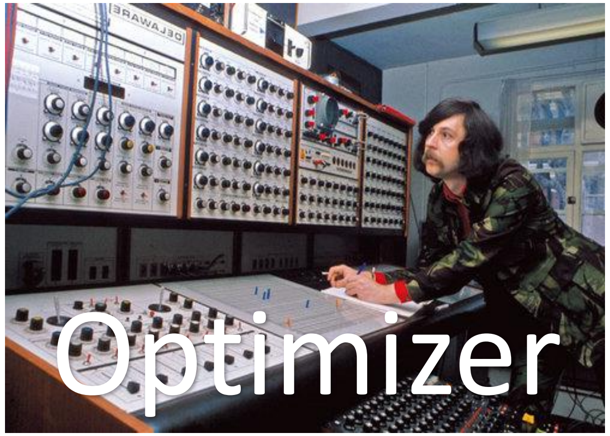
Max-heap:

- *O(log n)* per update
- *O(n)* per batch update (“heapify”)

Tuning Dyna

Solver has “knobs“ to tune





$$\rho(\pi) = \mathbb{E}\left[\sum_{i=1}^{\infty} \gamma^i \lambda_i \,\mathrm{latency}(i)\right]$$

Example knob: eager or lazy updates?
e.g., **dynamic max data structure**

```
% Dyna:
output max= input(I).
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Max-heap:

- *O(log n)* per update
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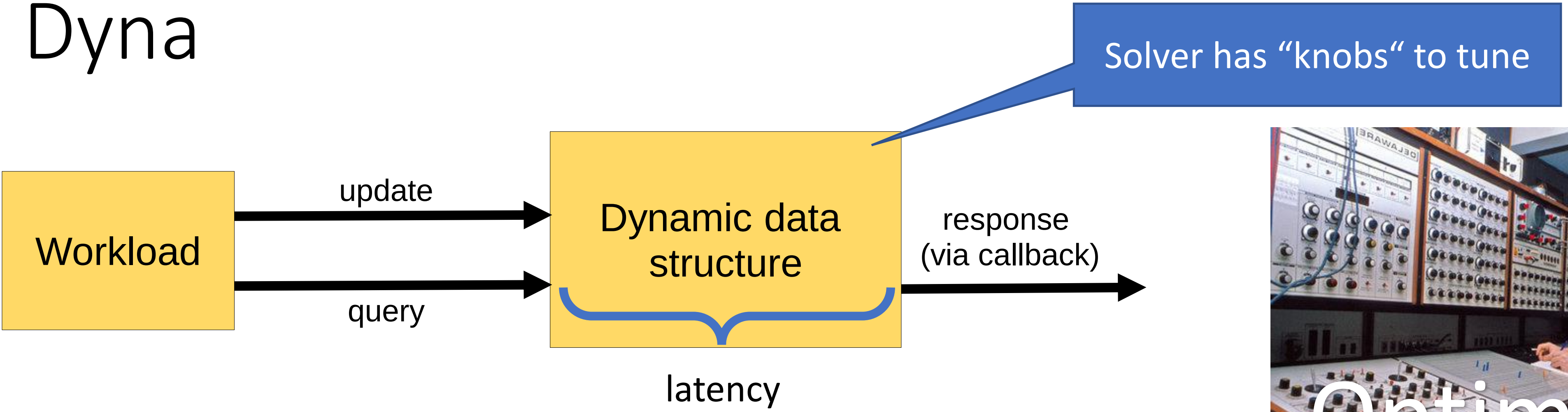
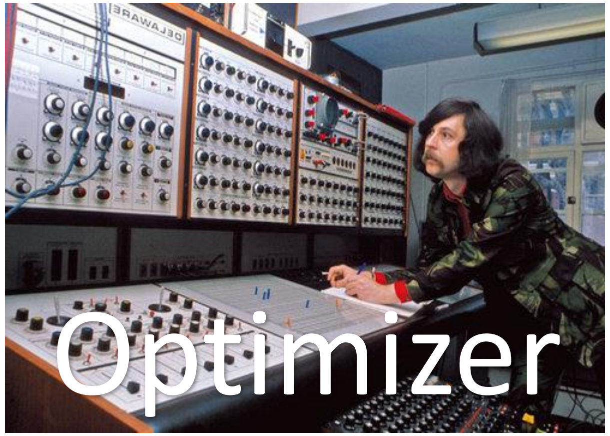
Tuning Dyna





Example knob: eager or lazy updates?
e.g., **dynamic max data structure**

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output max= input(I).
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Max-heap:

- *O(log n)* per update
- *O(n)* per batch update (“heapify”)

$$\rho(\pi) = \mathbb{E}\left[\sum_{i=1}^{\infty} \gamma^i \lambda_i \,\mathrm{latency}(i)\right]$$

knob settings

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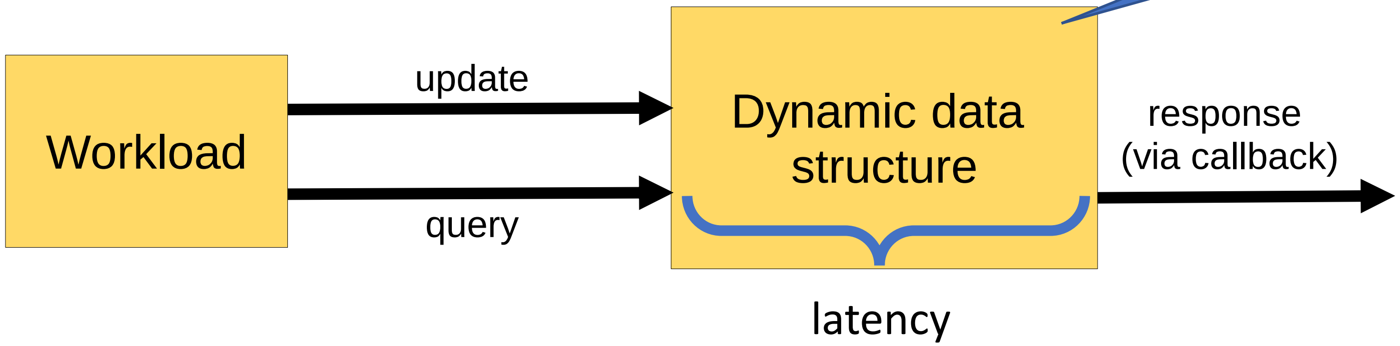
Solver has “knobs“ to tune



Workload

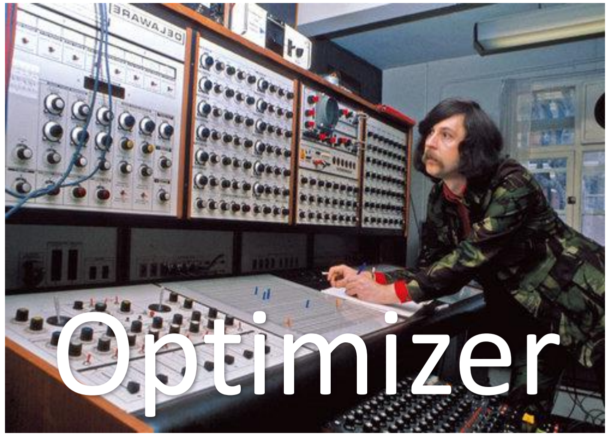
update

query

Dynamic data structure

response (via callback)

latency



Total cost knob setting
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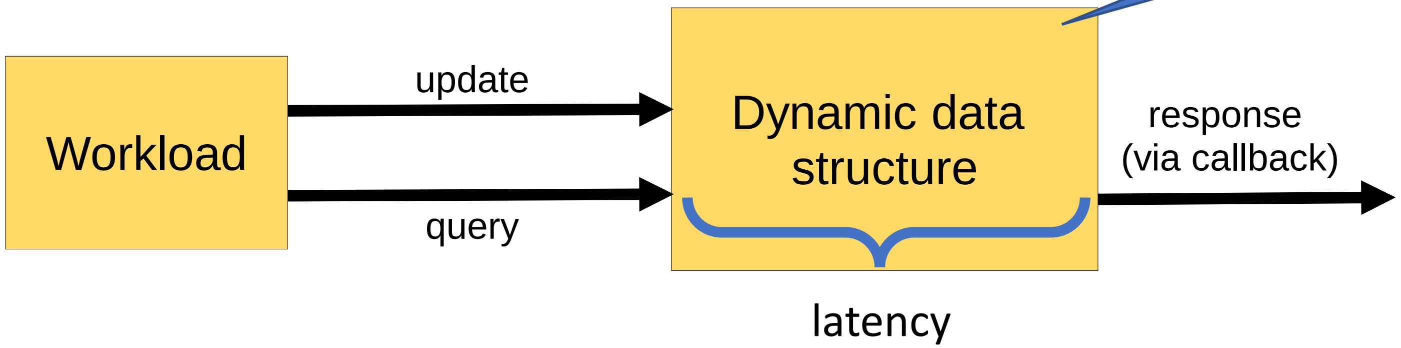

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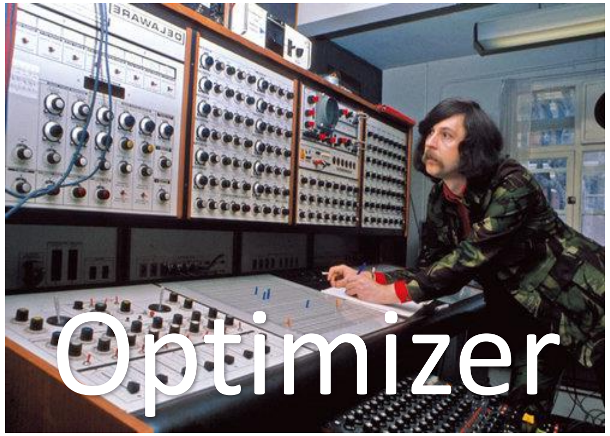

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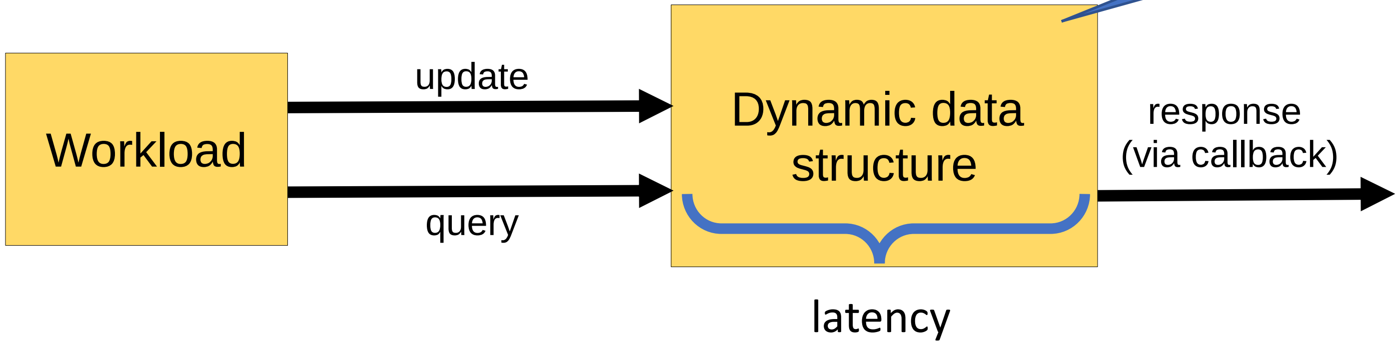

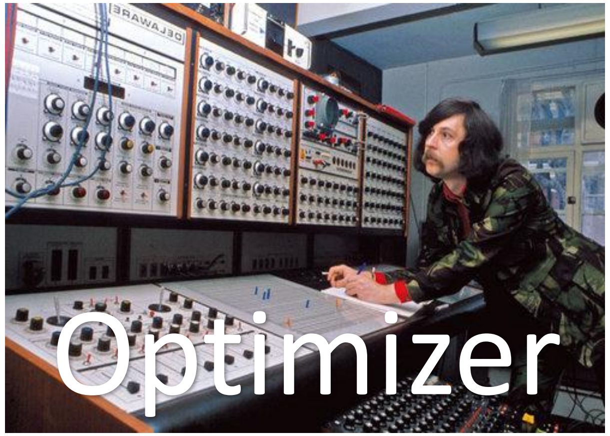

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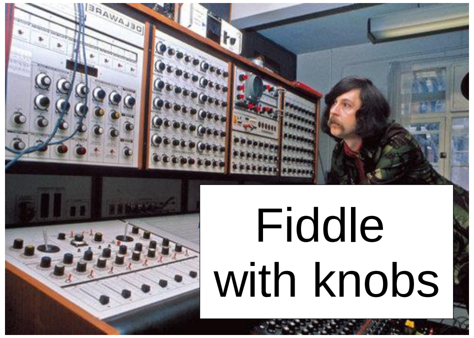

Fiddle
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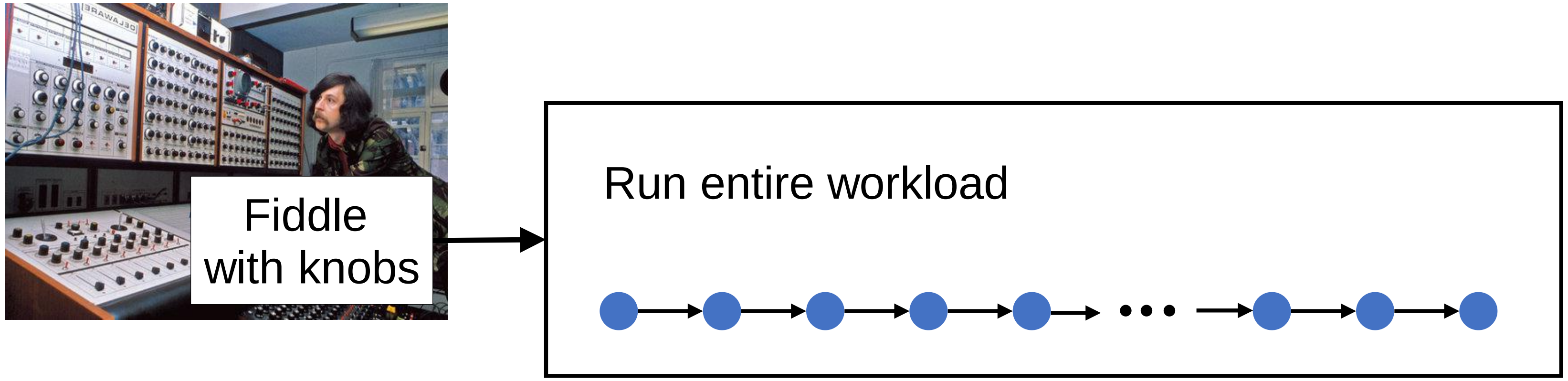

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Run entire workload

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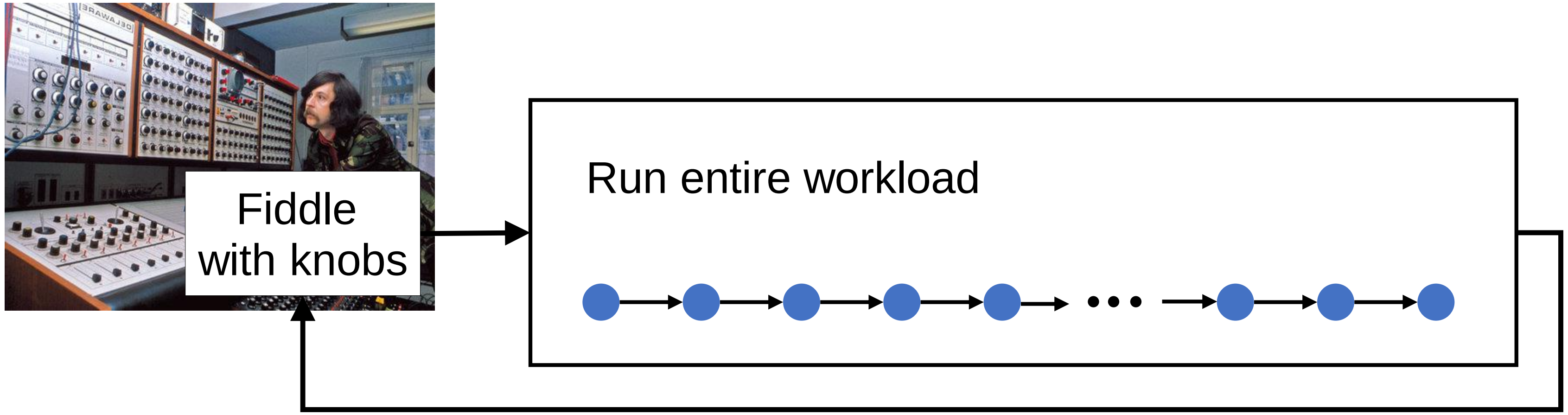

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Feedback $\rho(\pi)$

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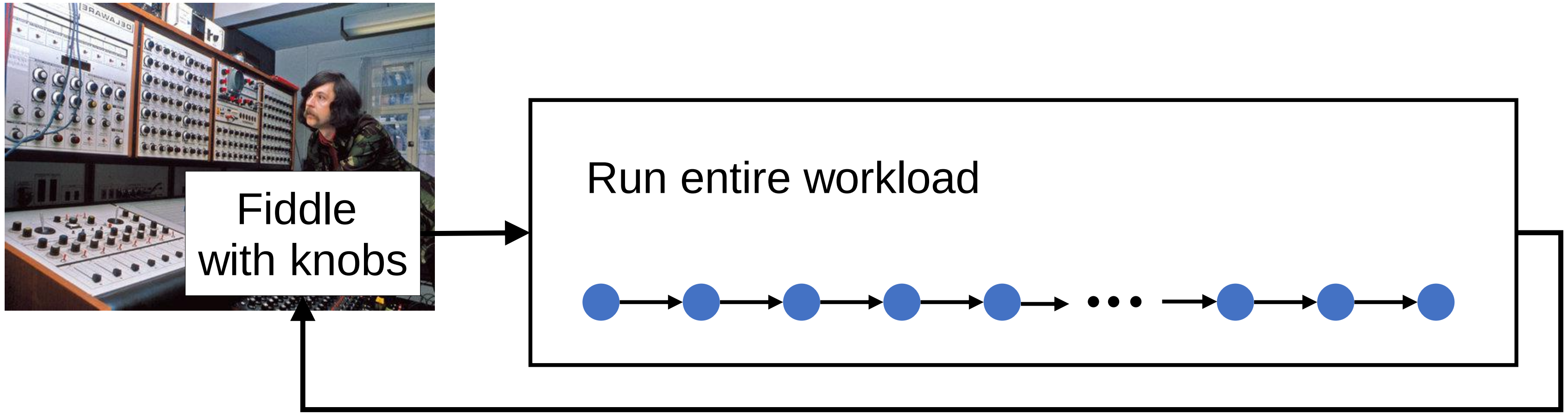

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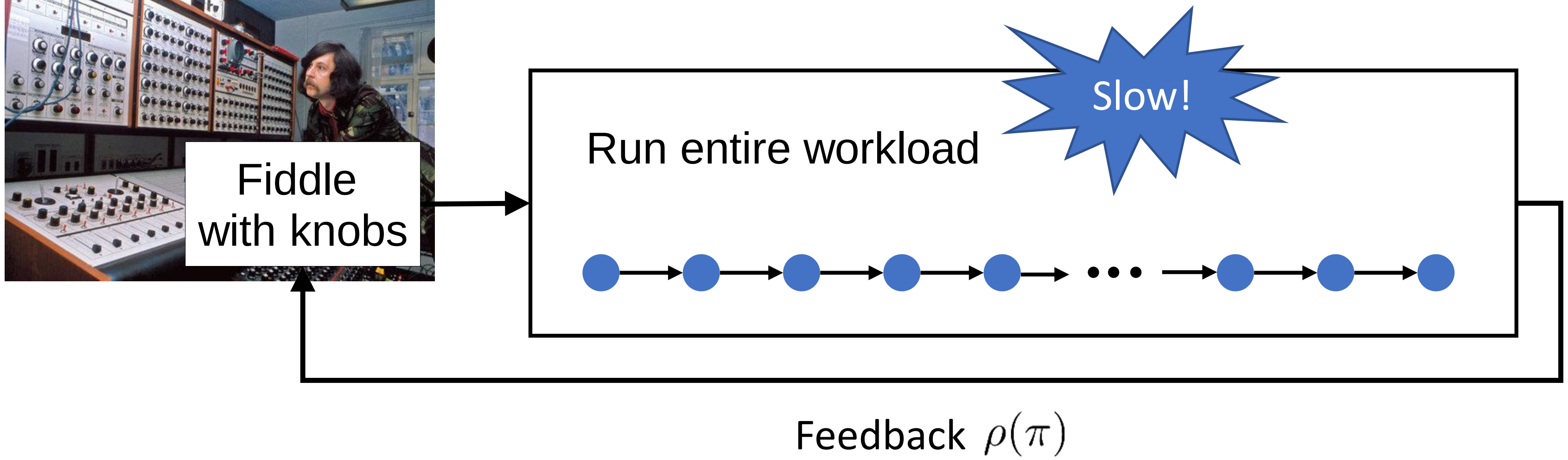

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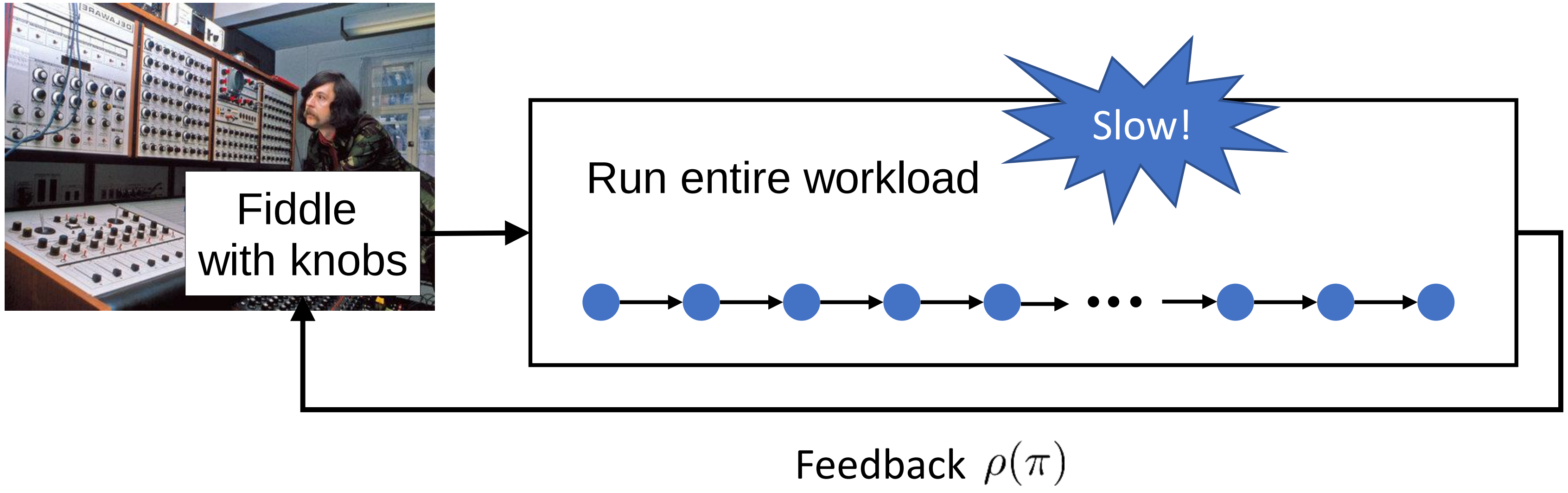

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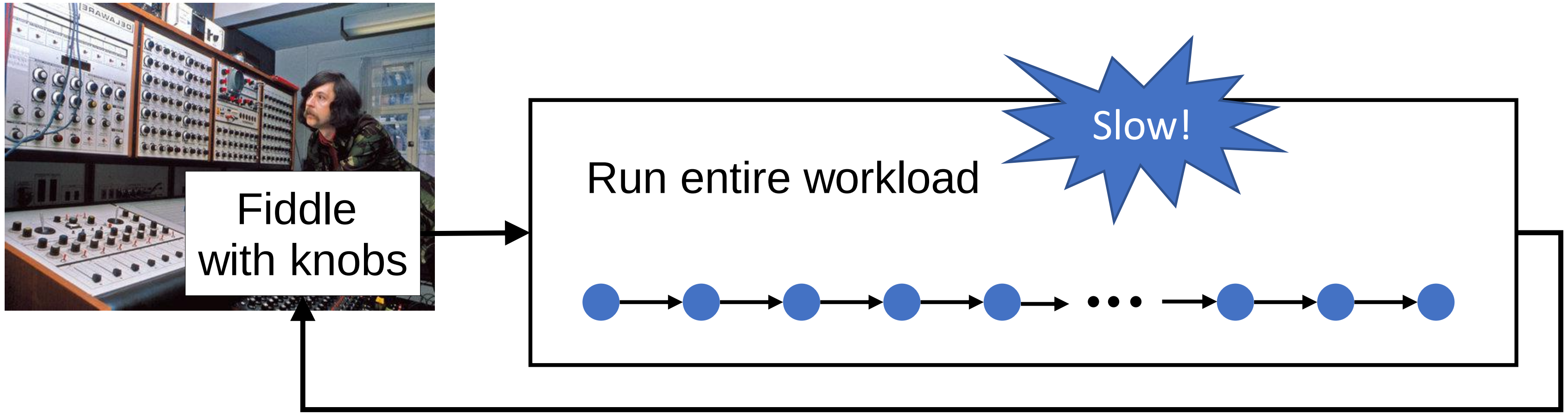

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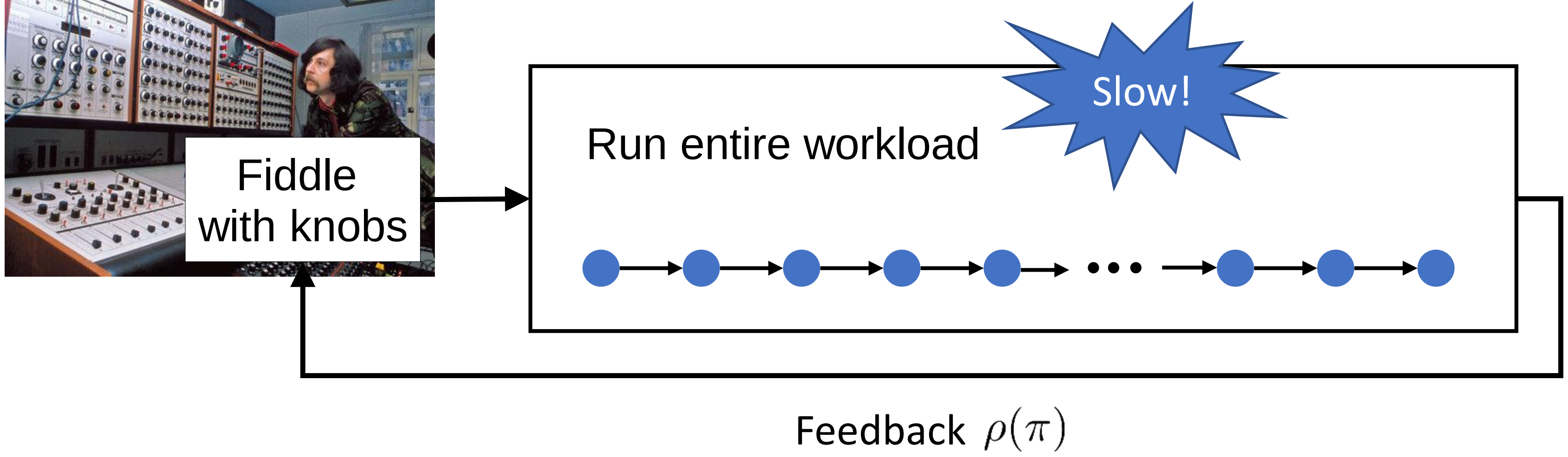

Open up the solver

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Inside the solver

queries & updates

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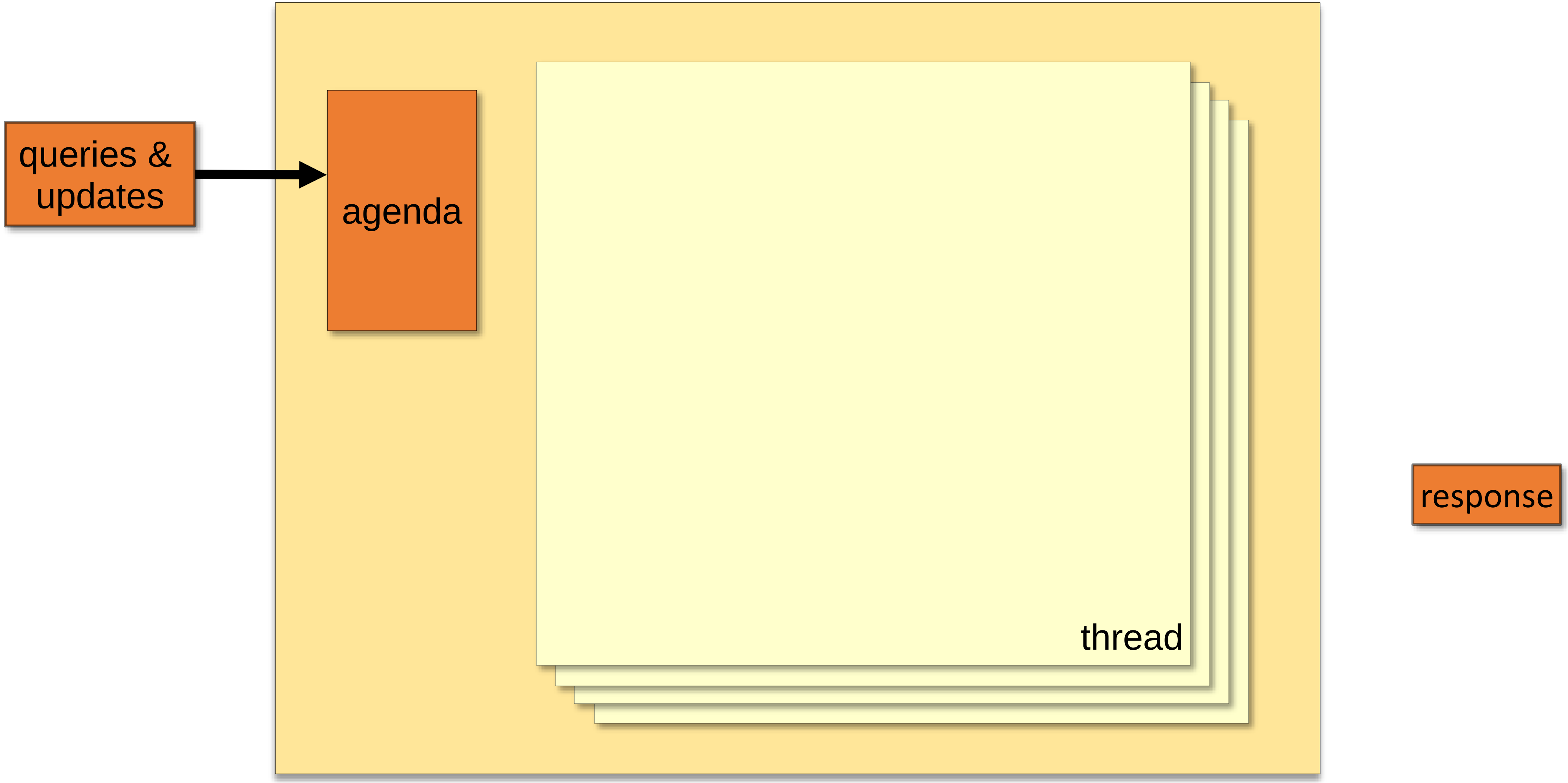

queries & updates

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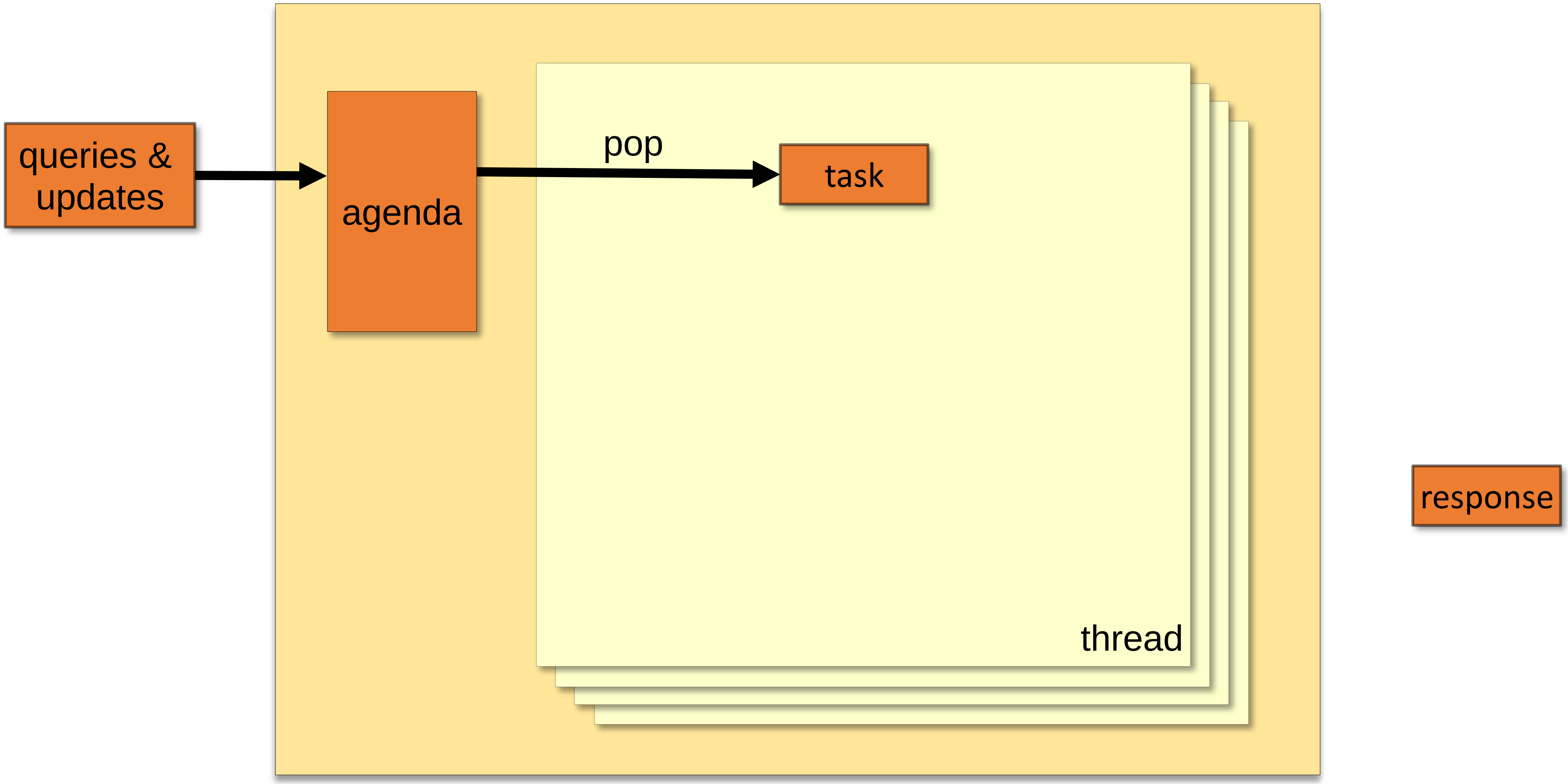

queries & updates

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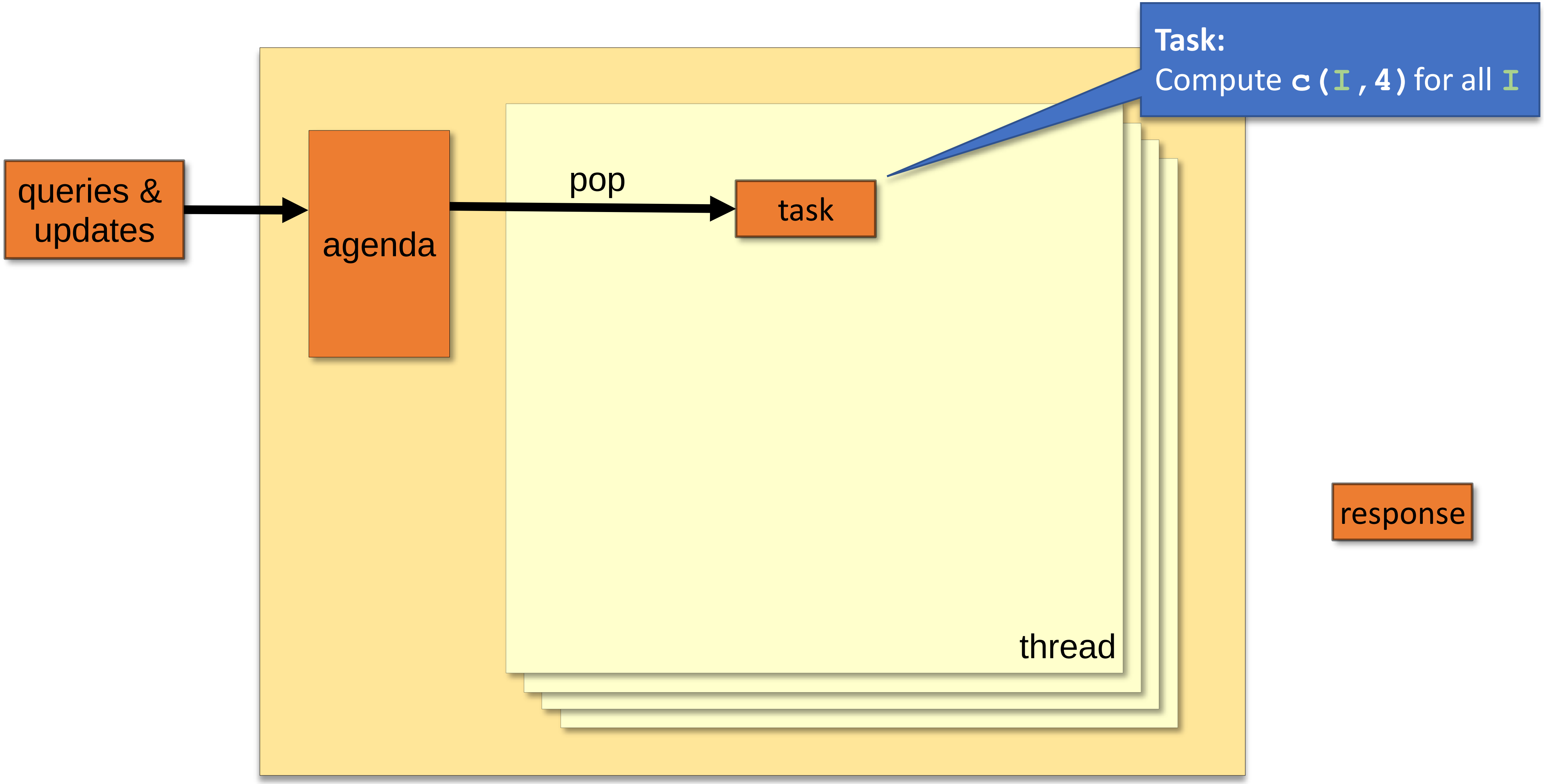

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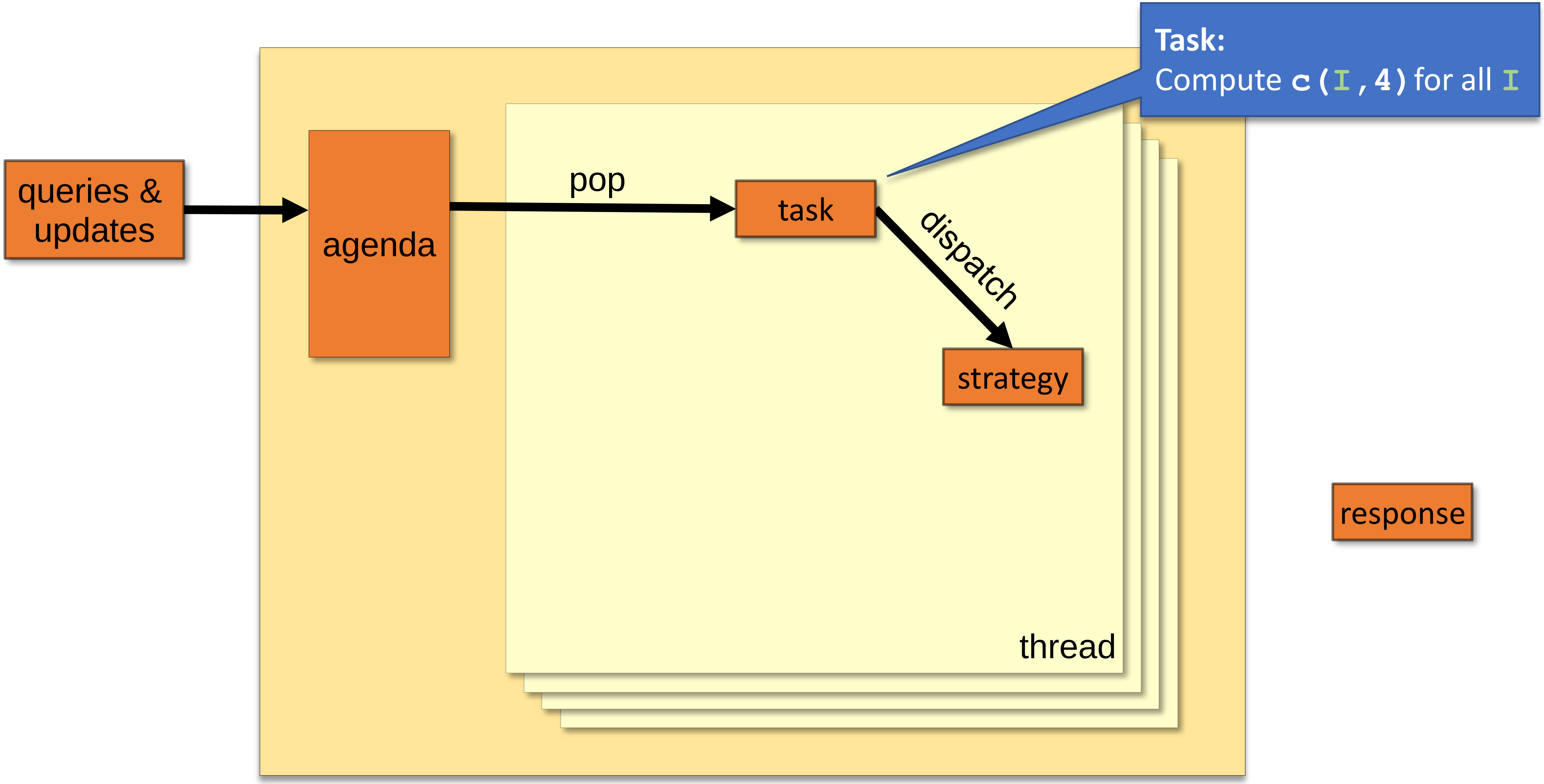

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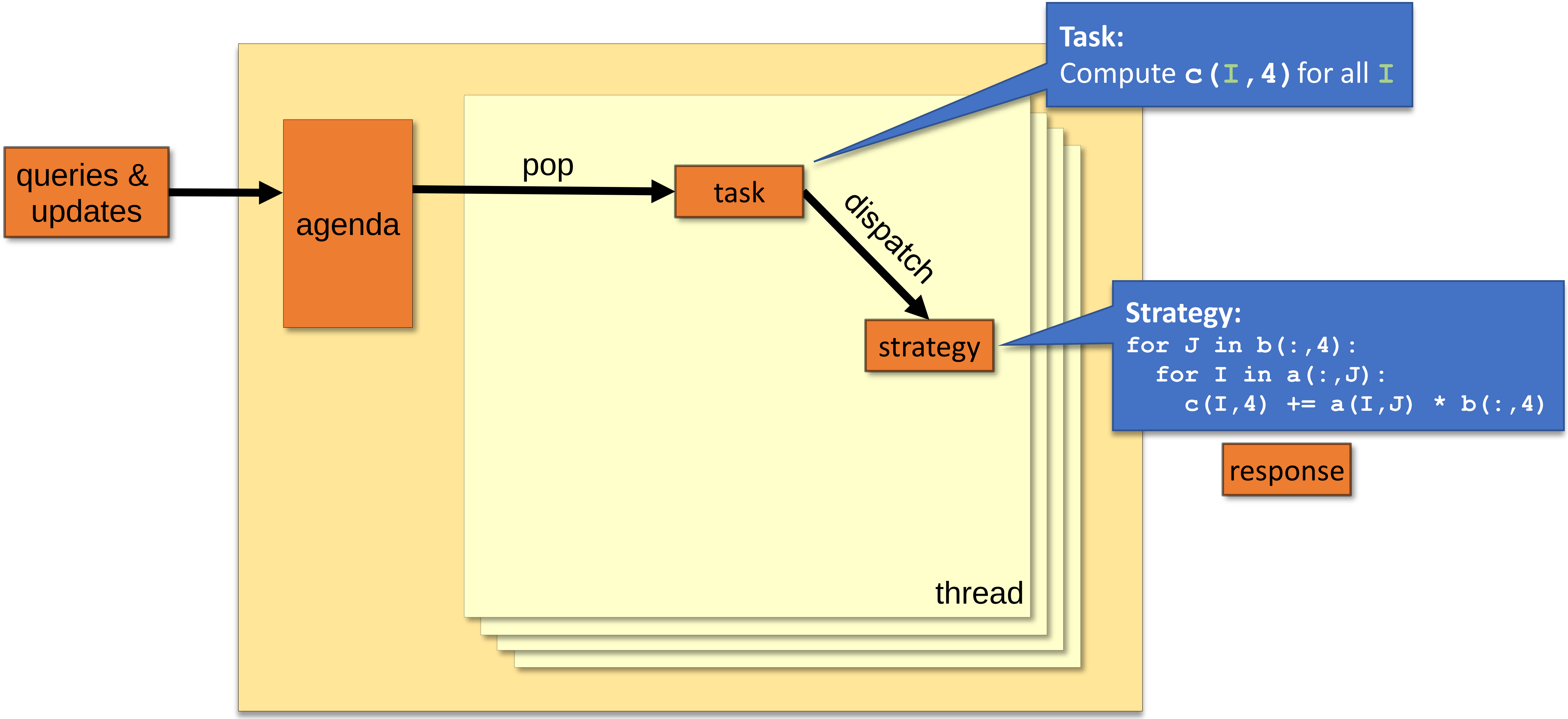

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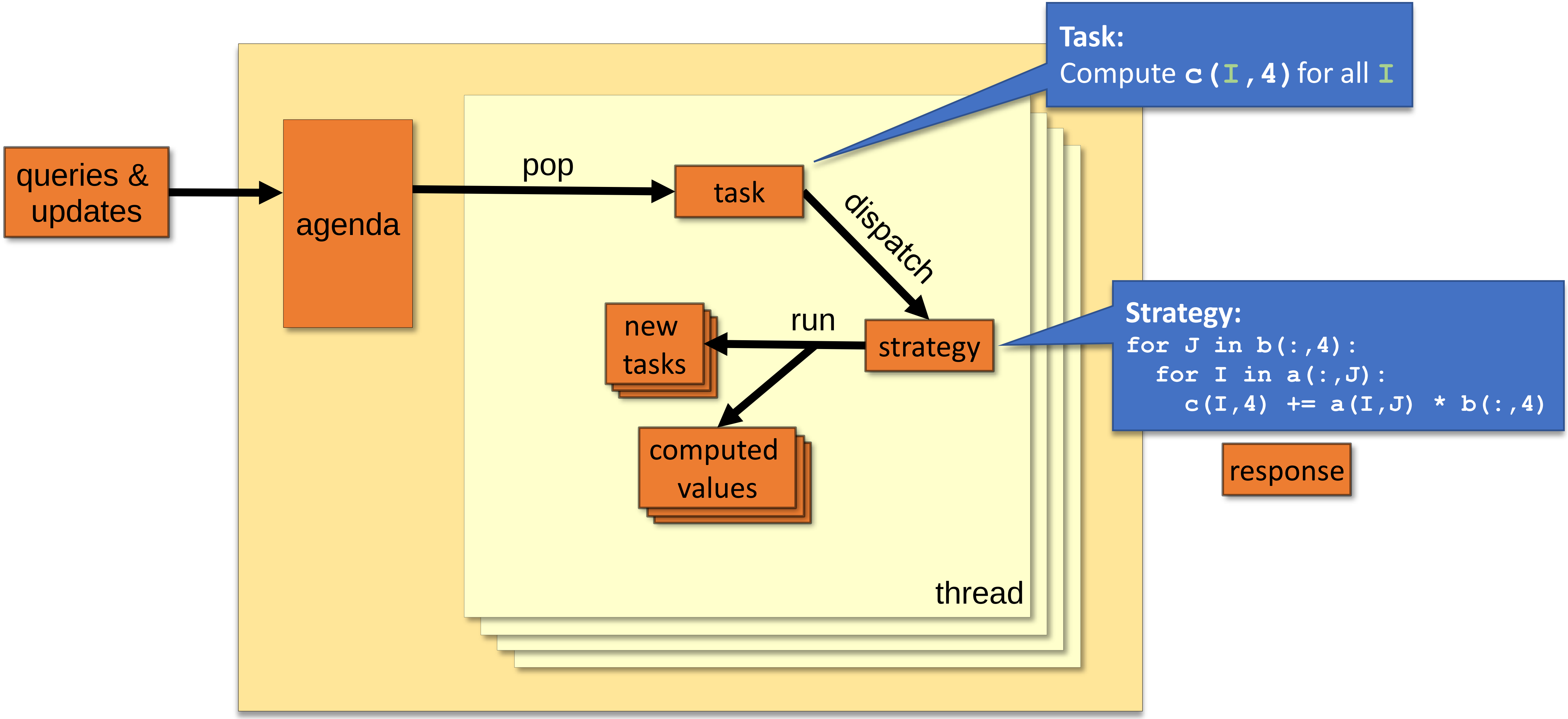

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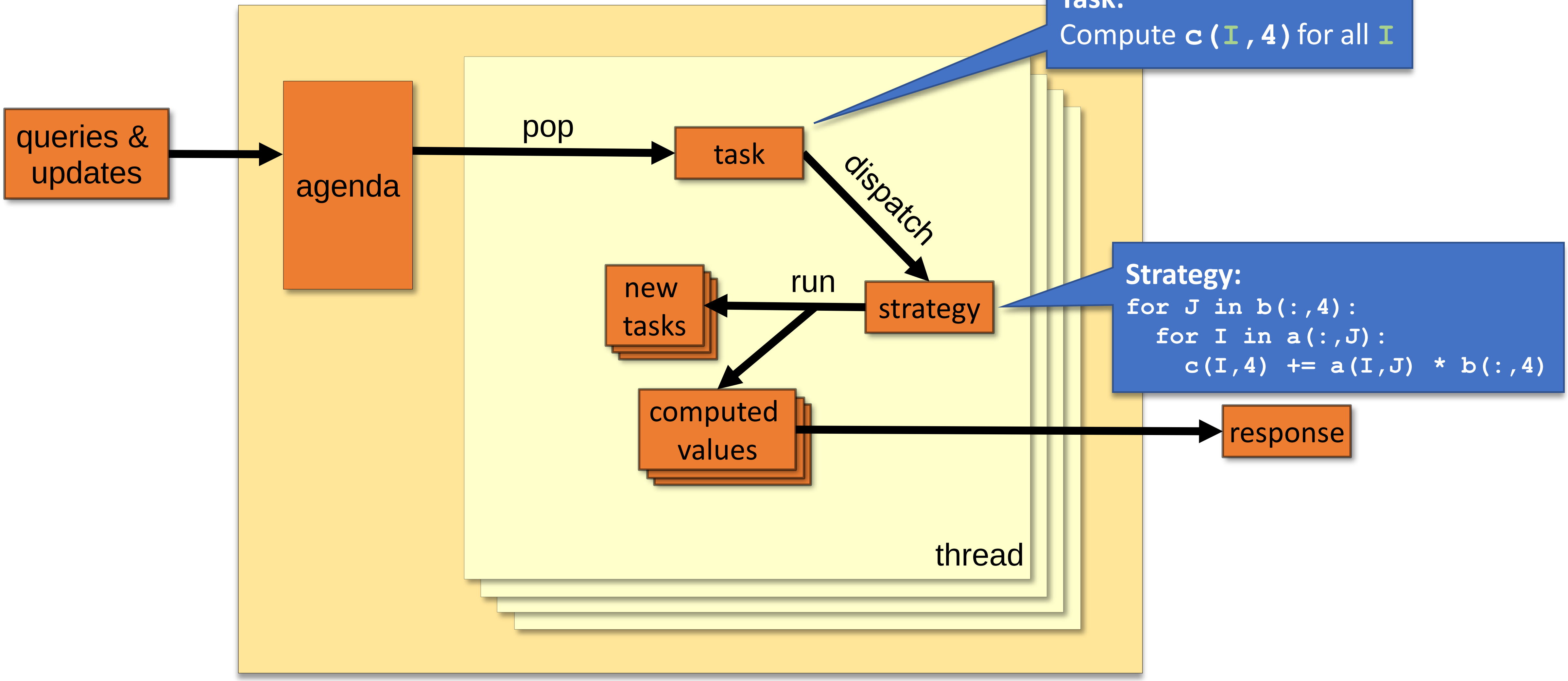

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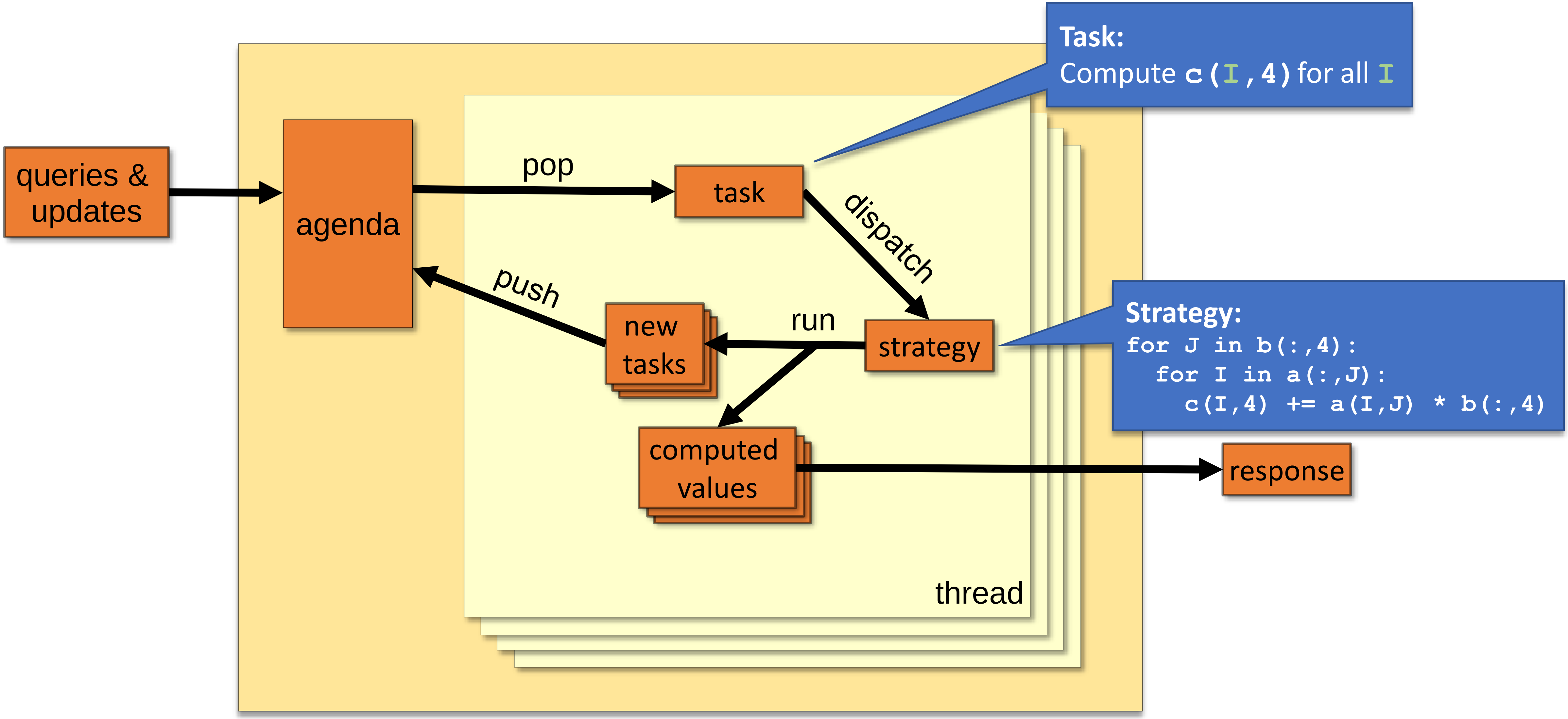

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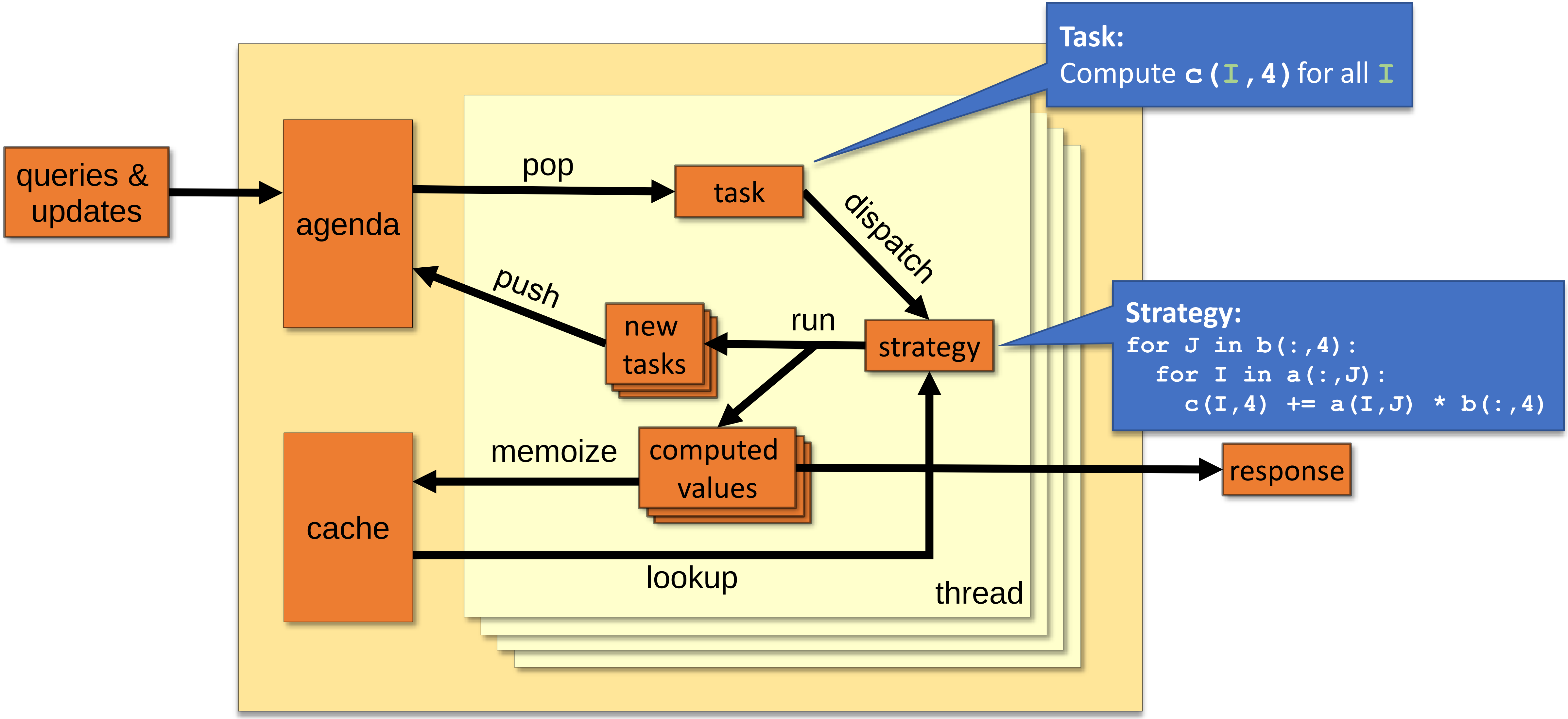

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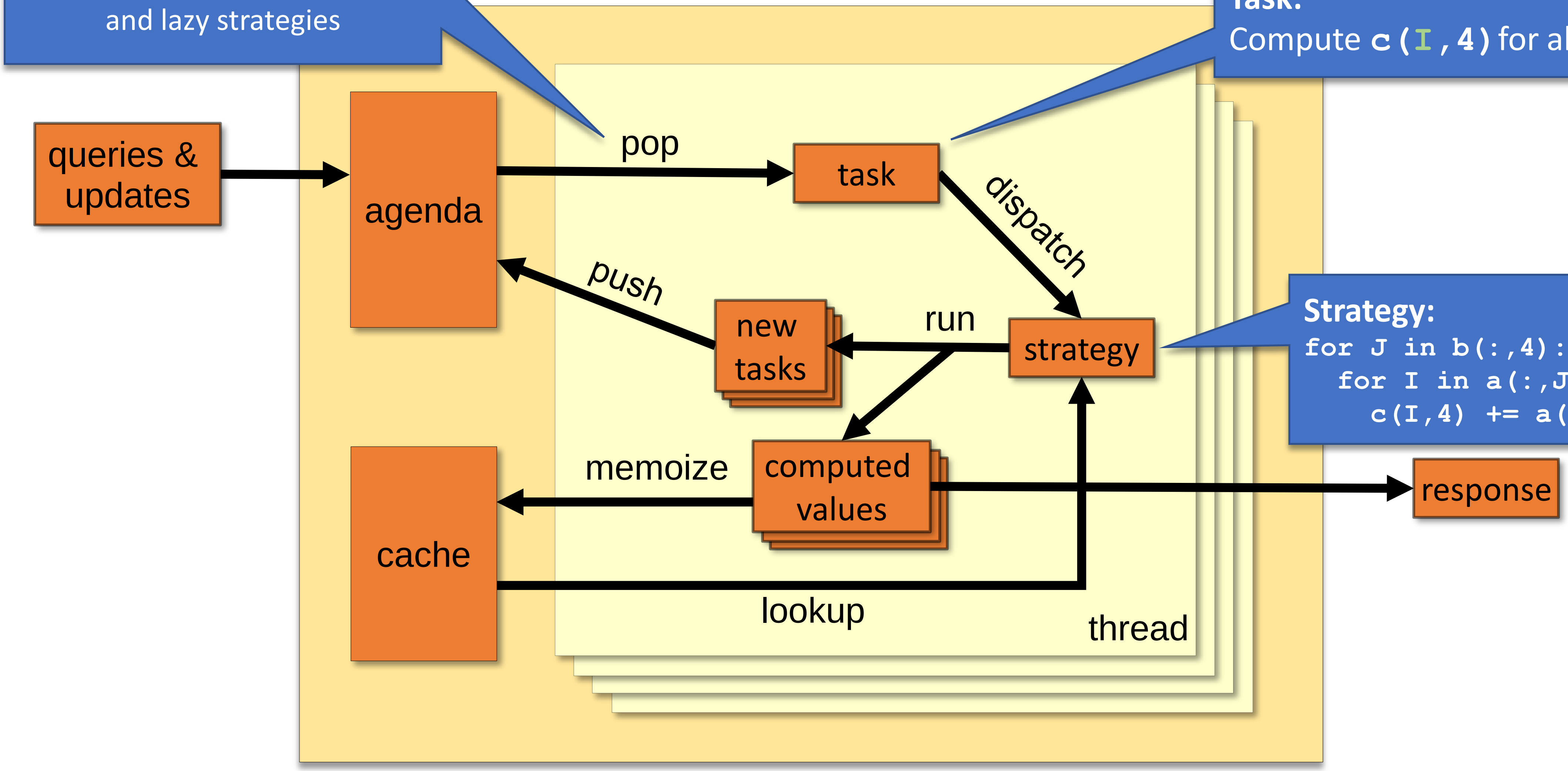

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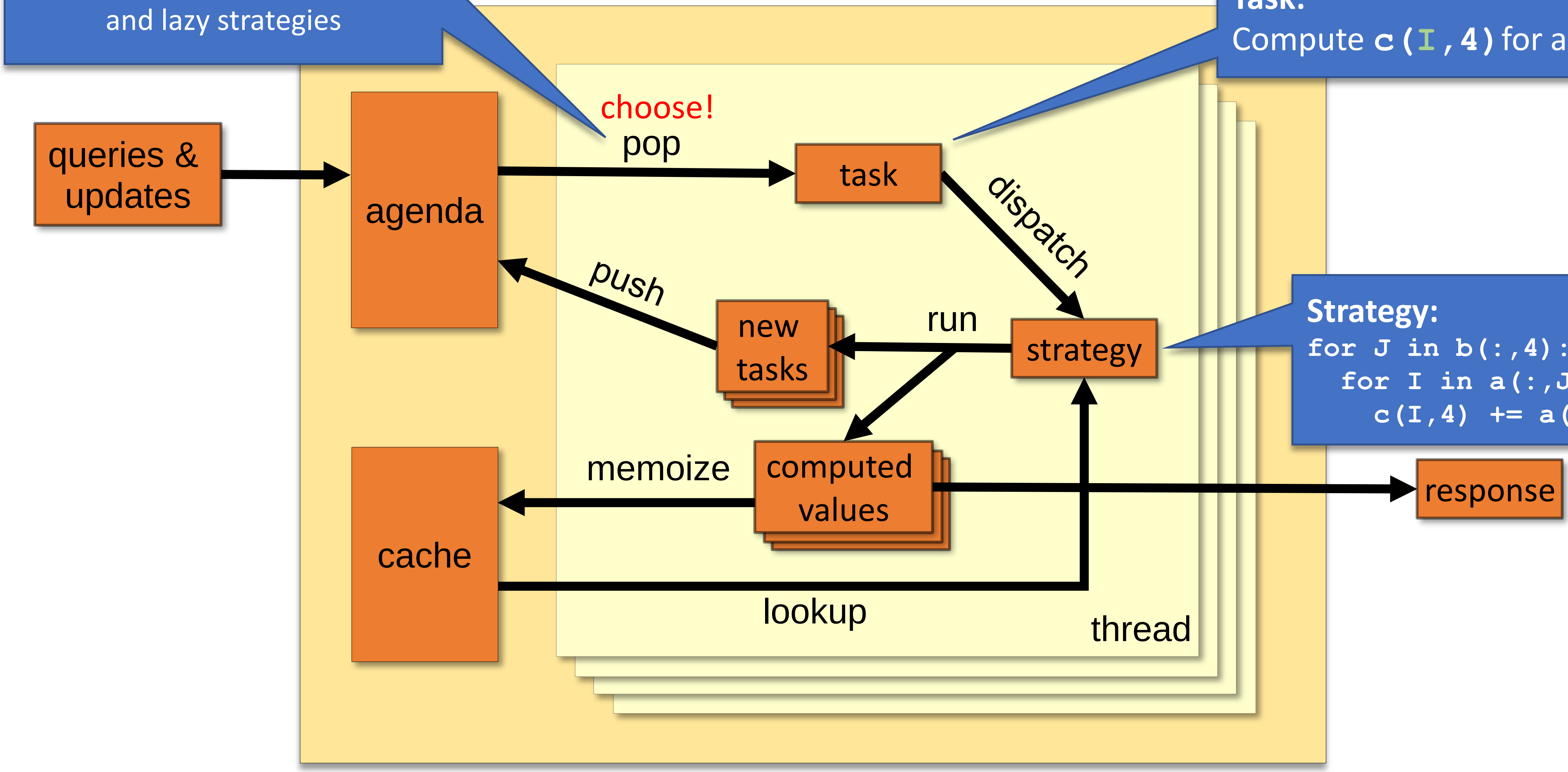

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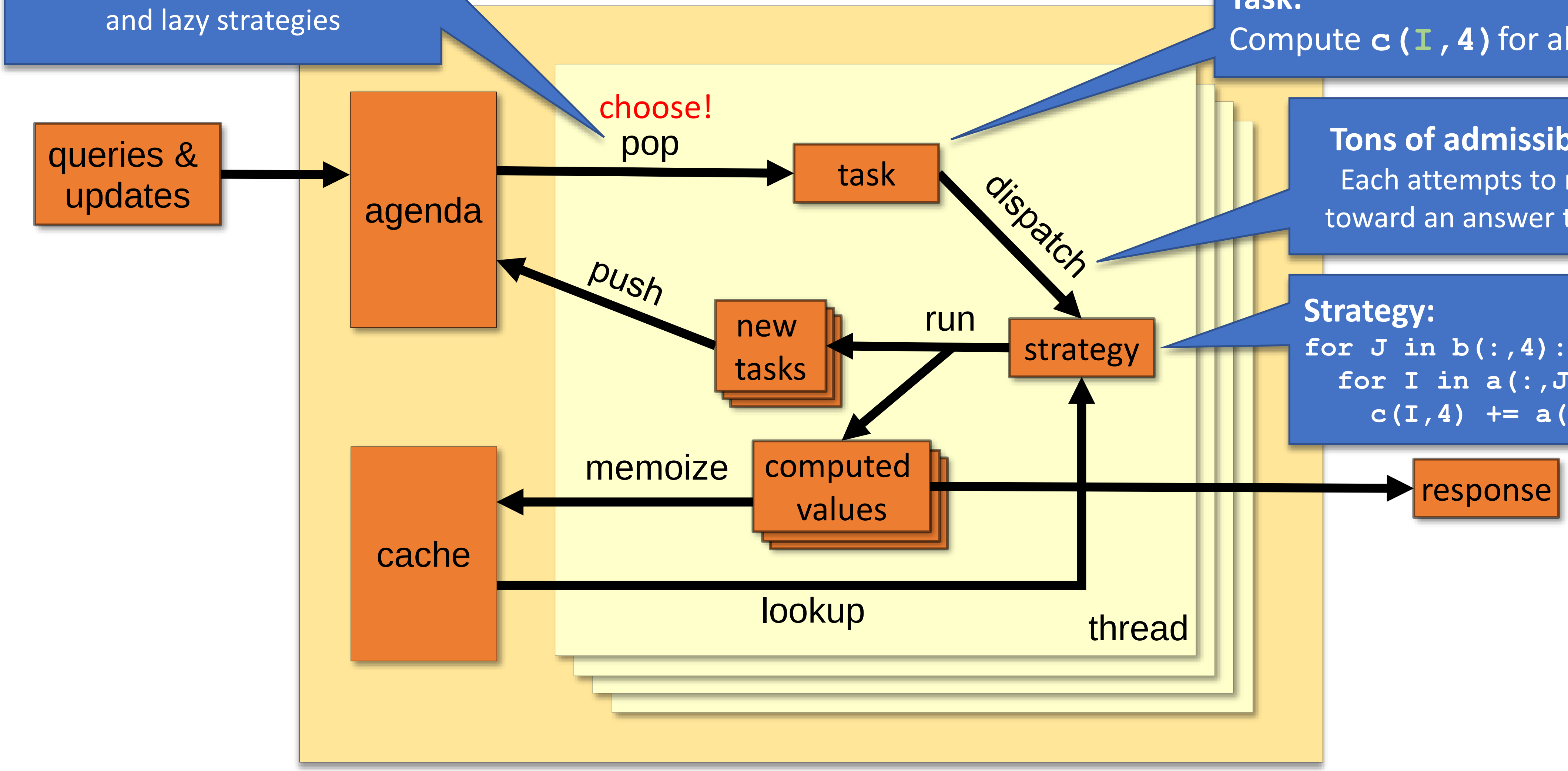

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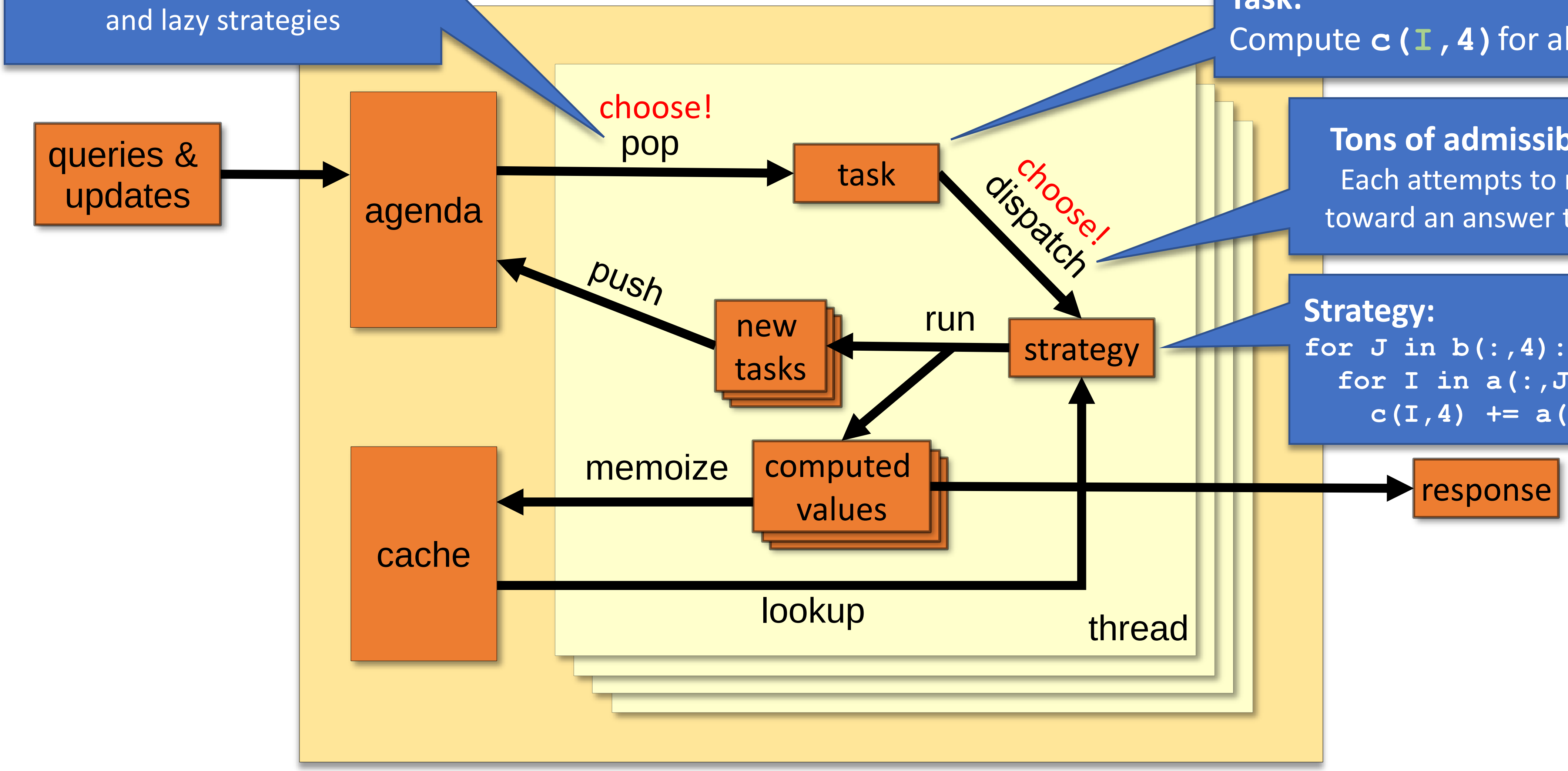

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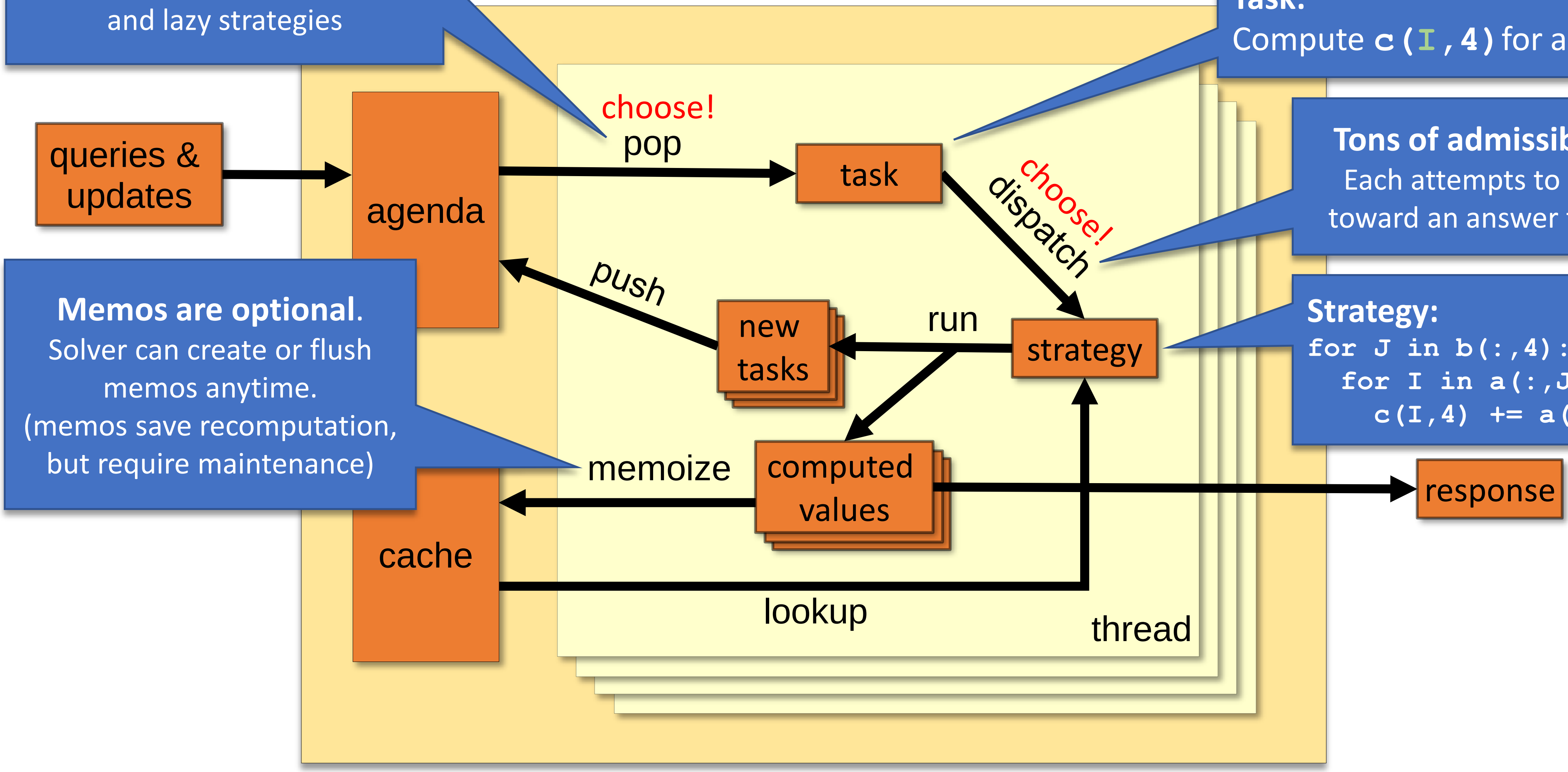

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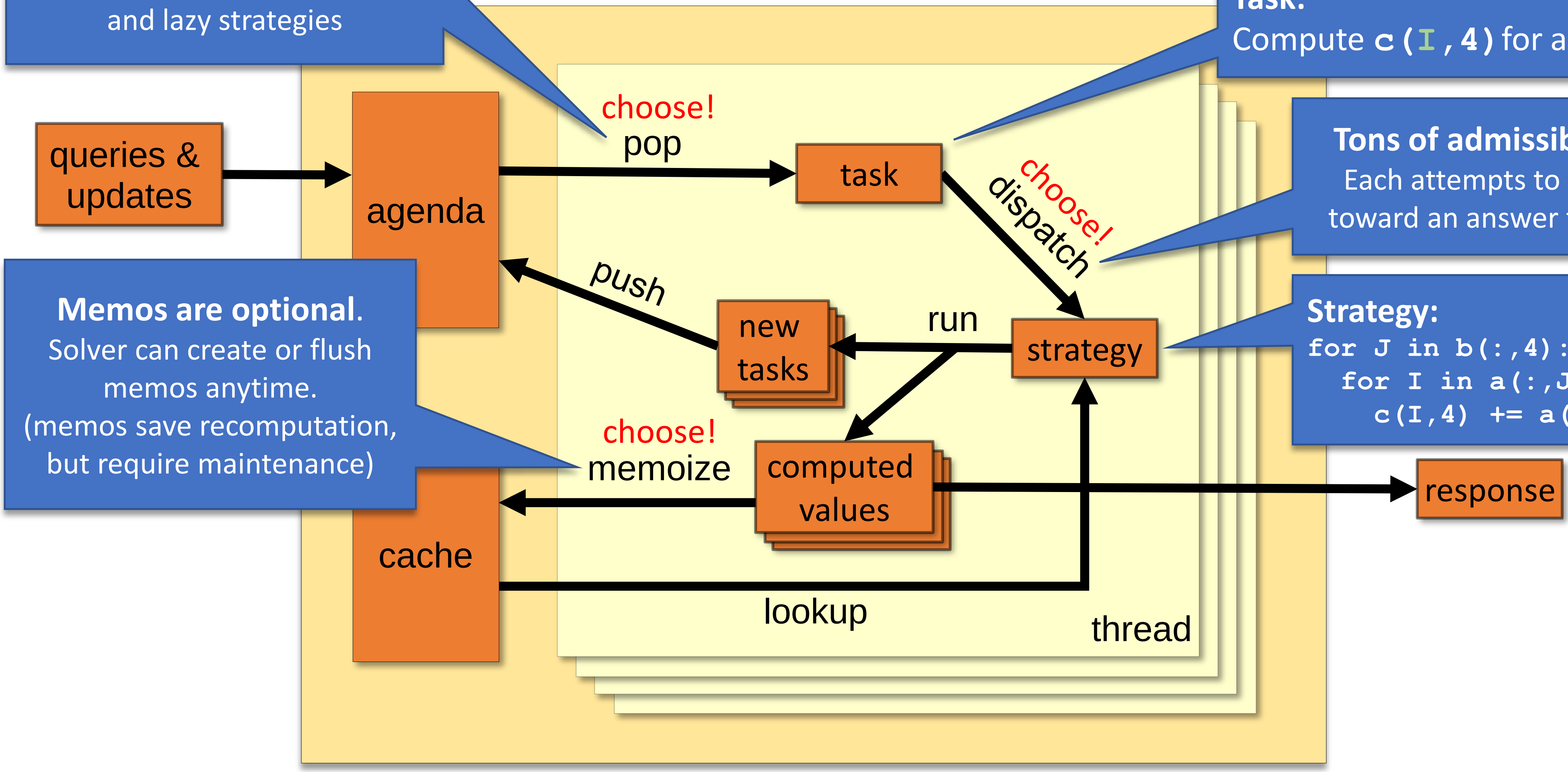

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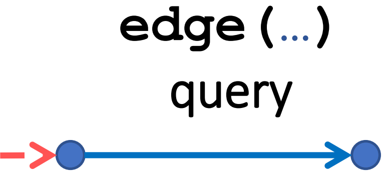

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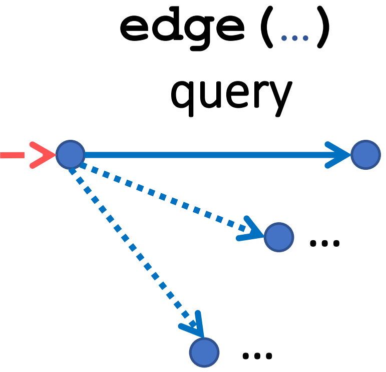

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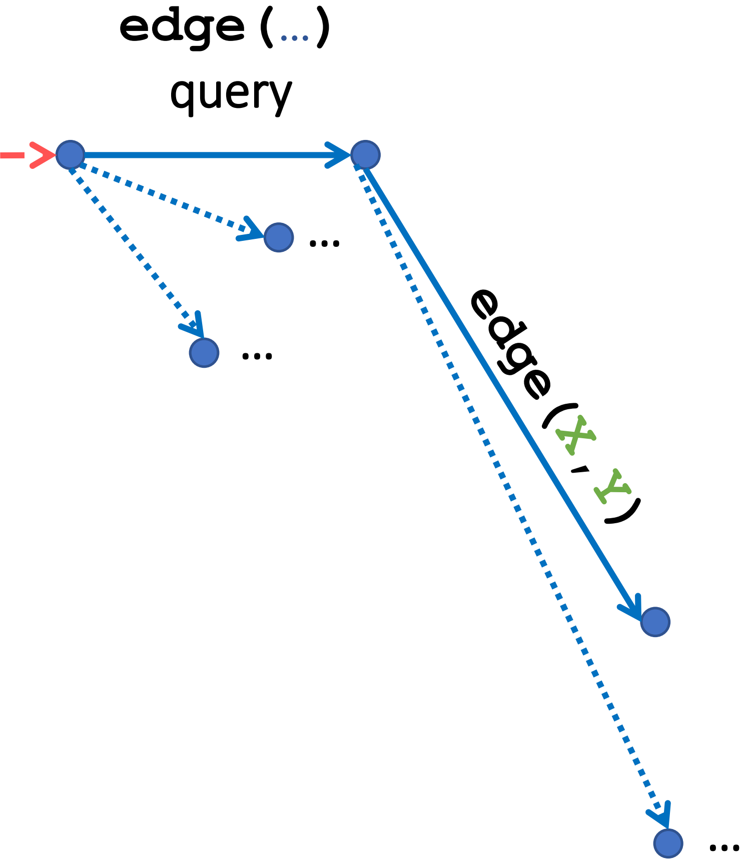

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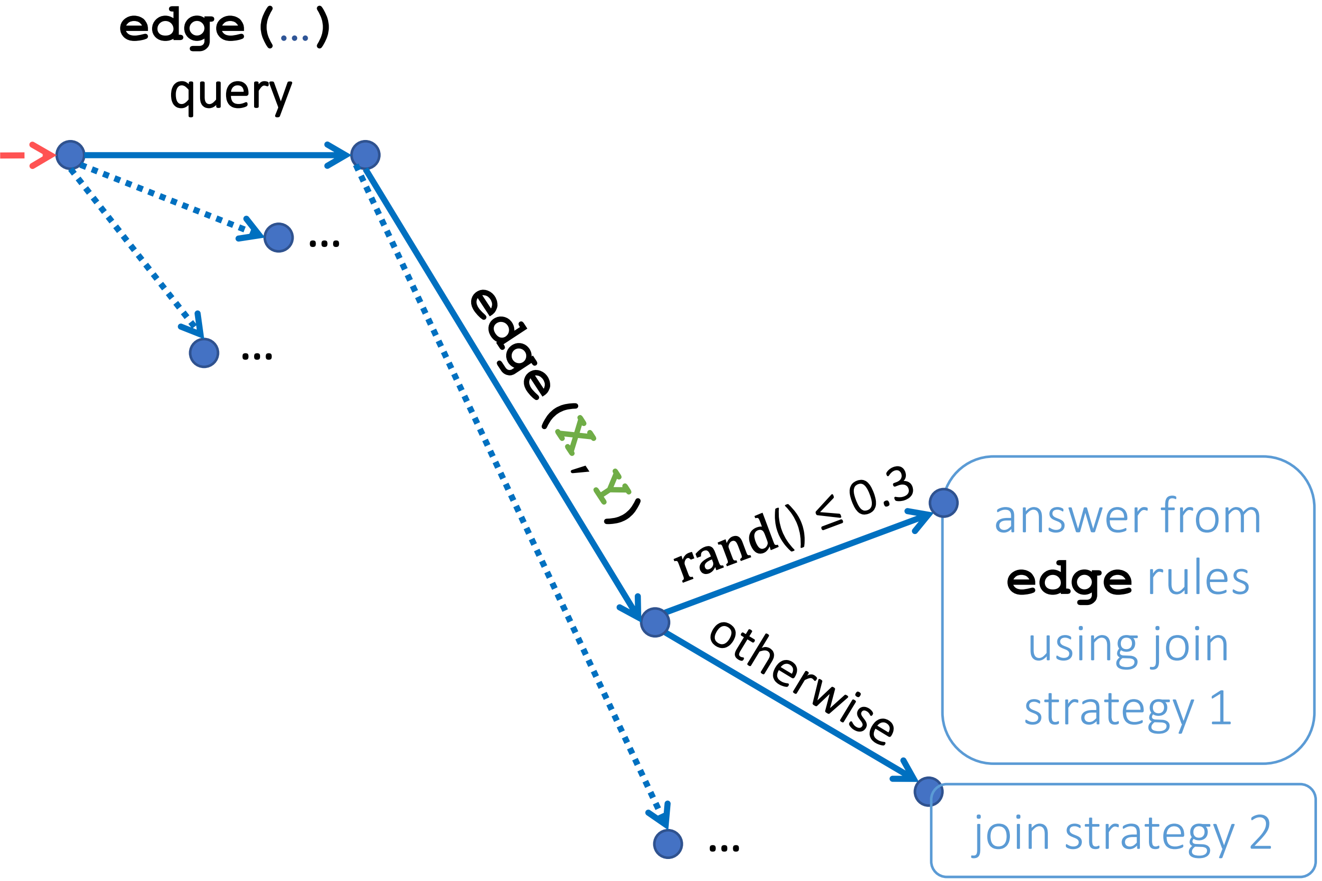
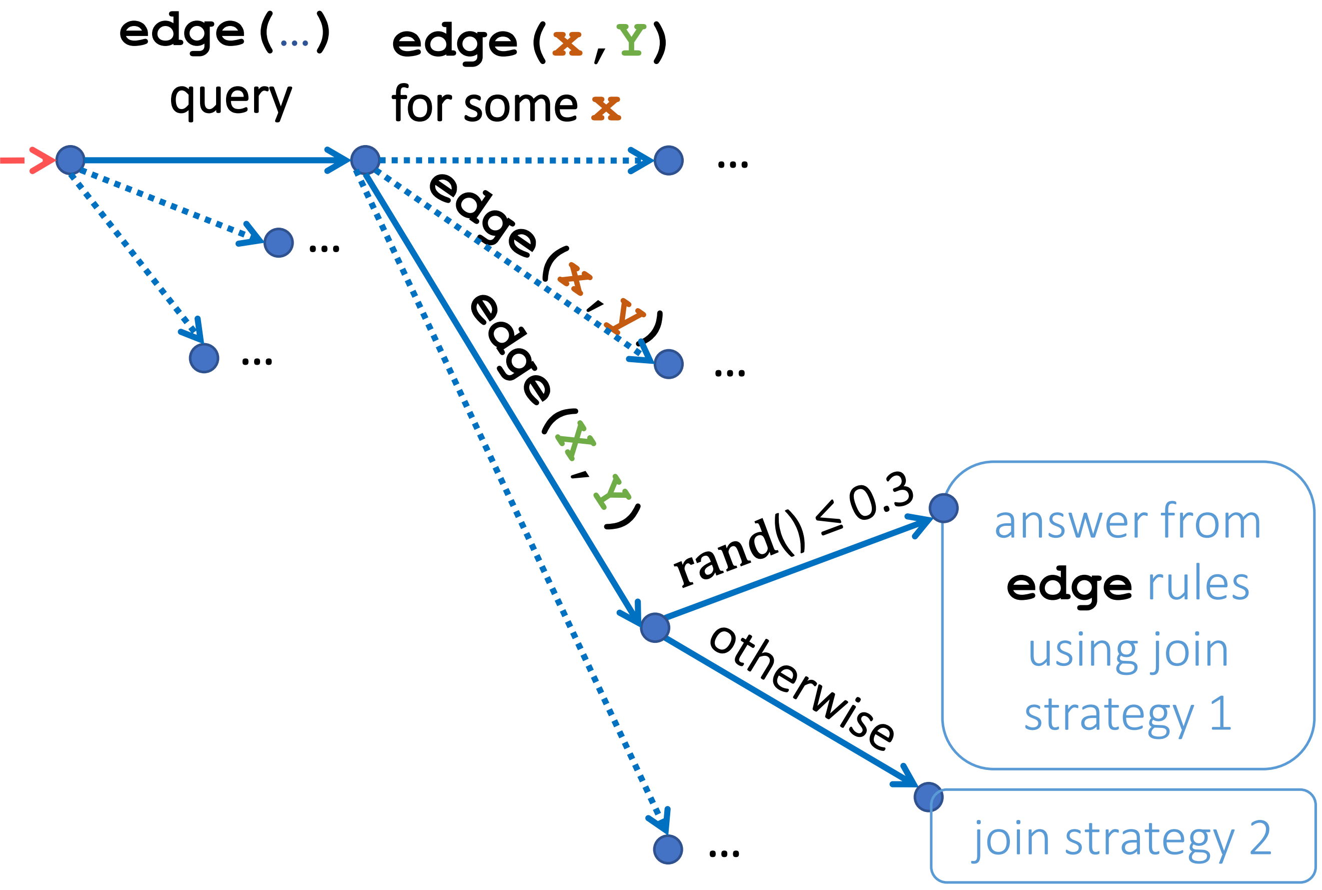


answer from **edge** rules using join strategy 1

join strategy 2

Sequential choices at runtime (some stochastic)



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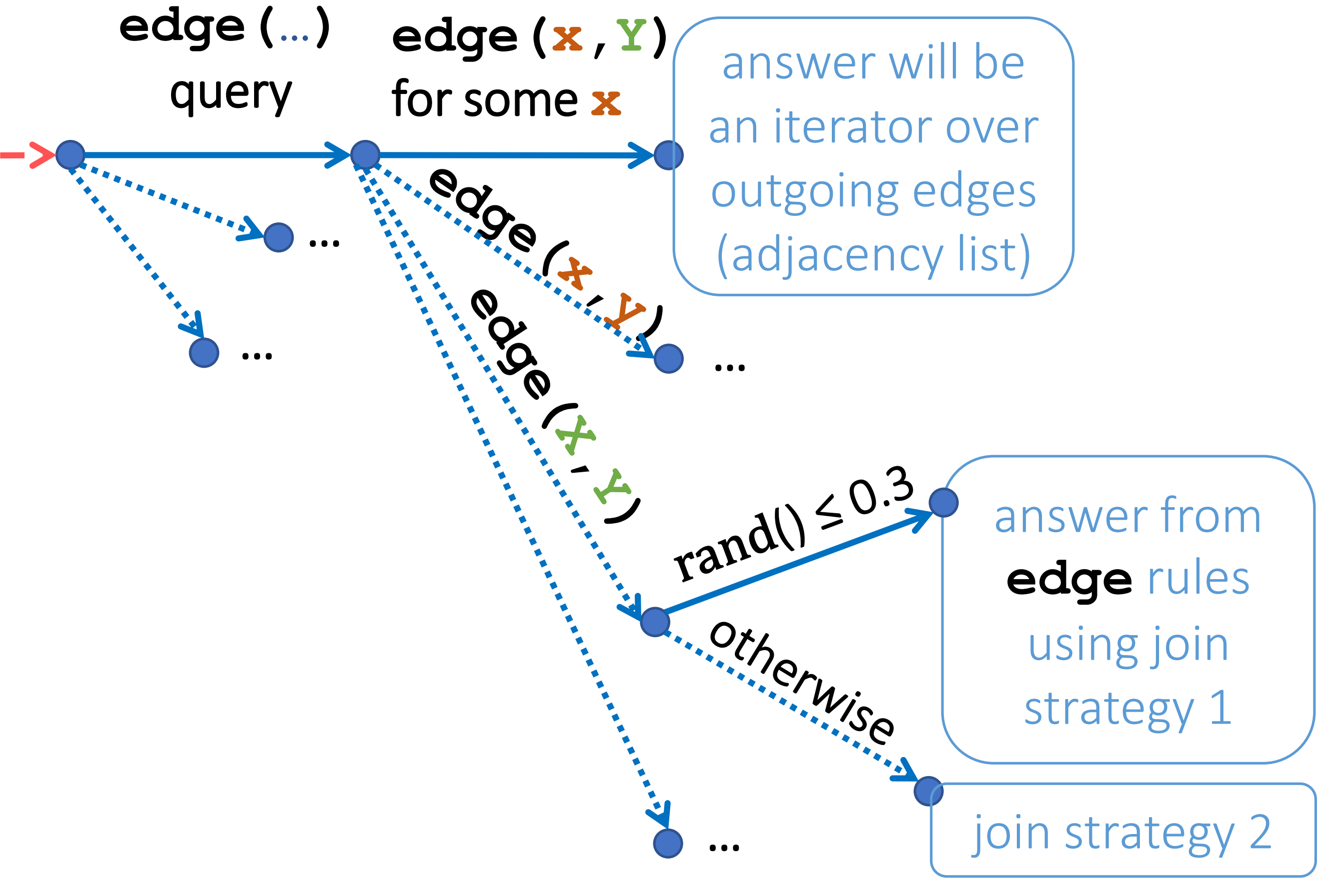

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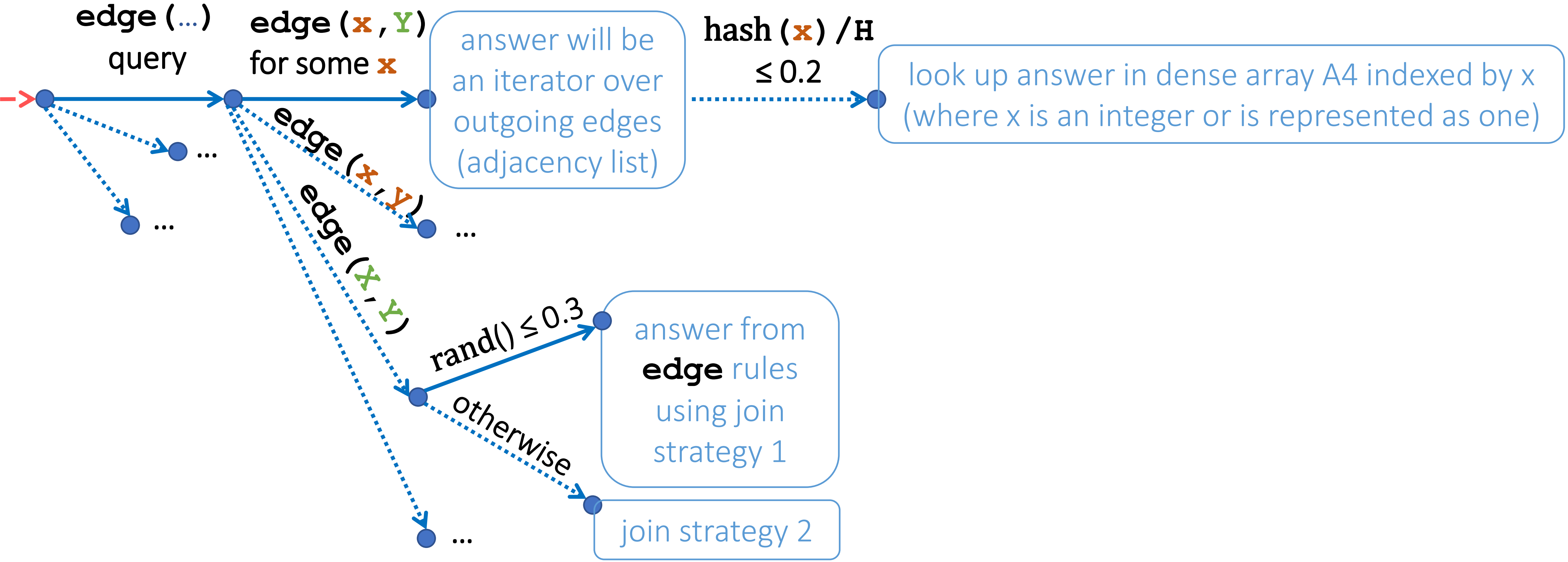

edge(...) query

edge(x,Y) for some x

answer will be an iterator over outgoing edges (adjacency list)

hash(x)/H ≤ 0.2

look up answer in dense array A4 indexed by x (where x is an integer or is represented as one)

edge(x,Y)

edge(X,Y)

rand() ≤ 0.3

answer from **edge** rules using join strategy 1

otherwise

join strategy 2

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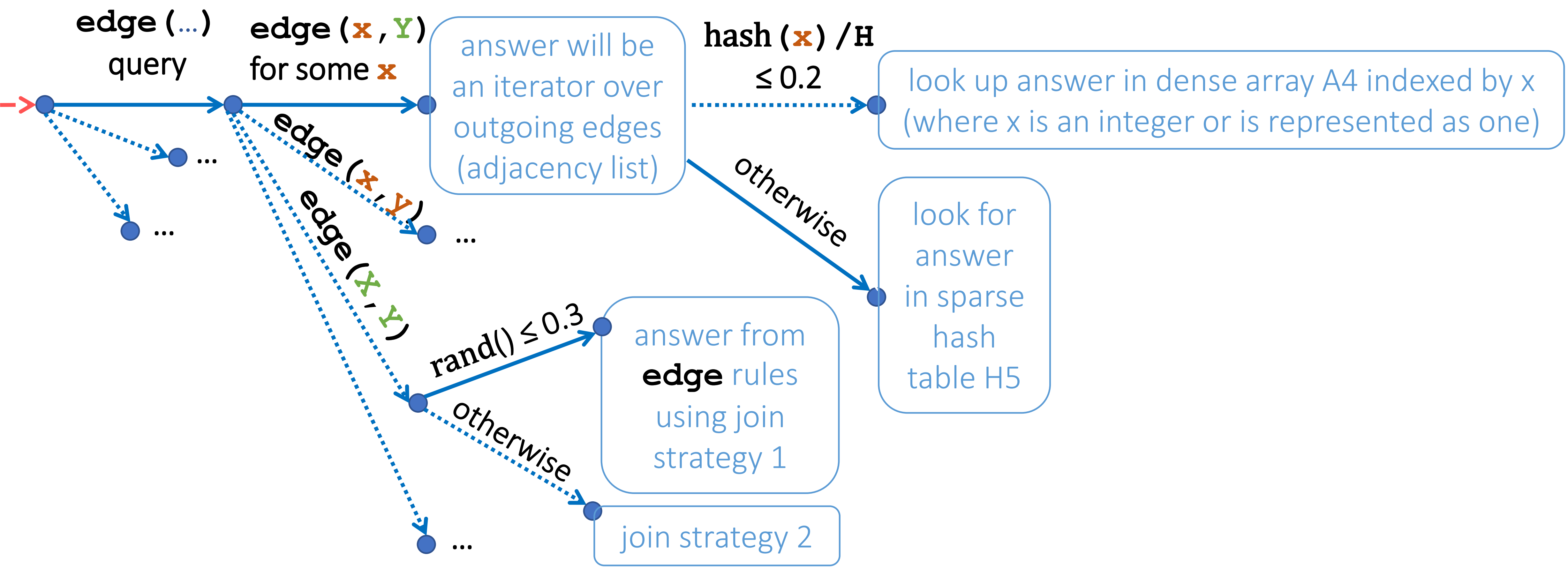

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…

…

…

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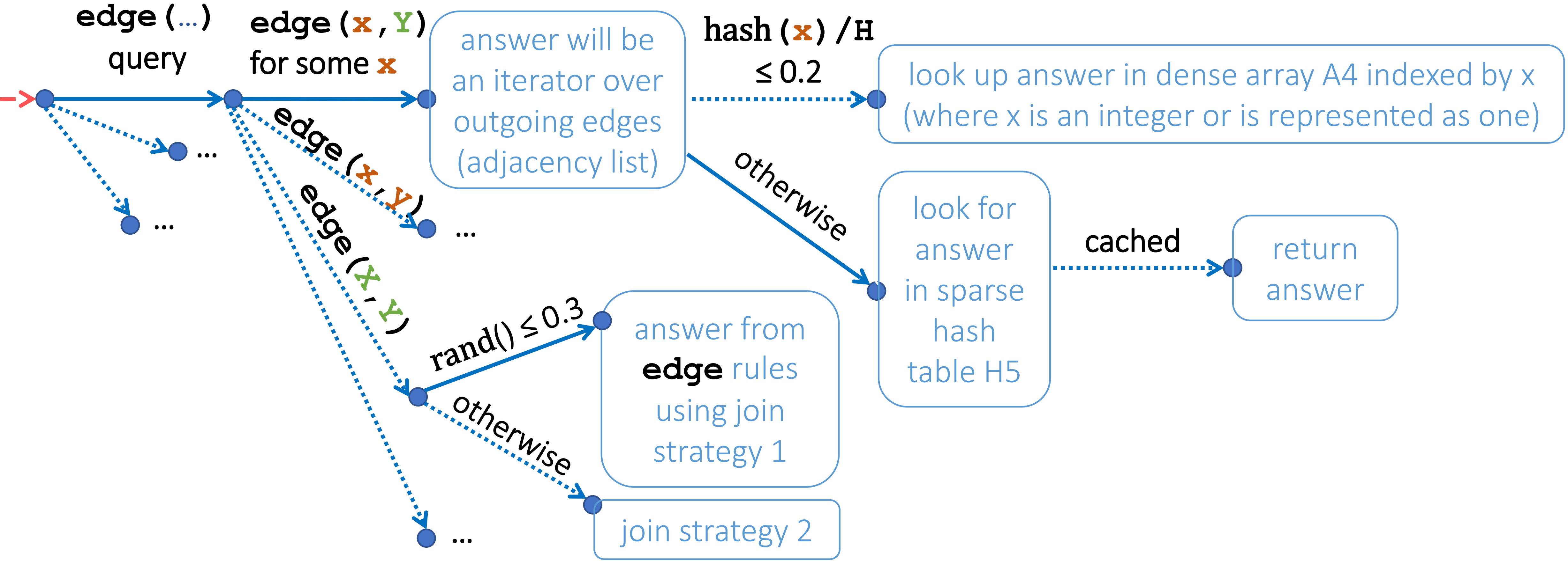

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…

…

…

…

…

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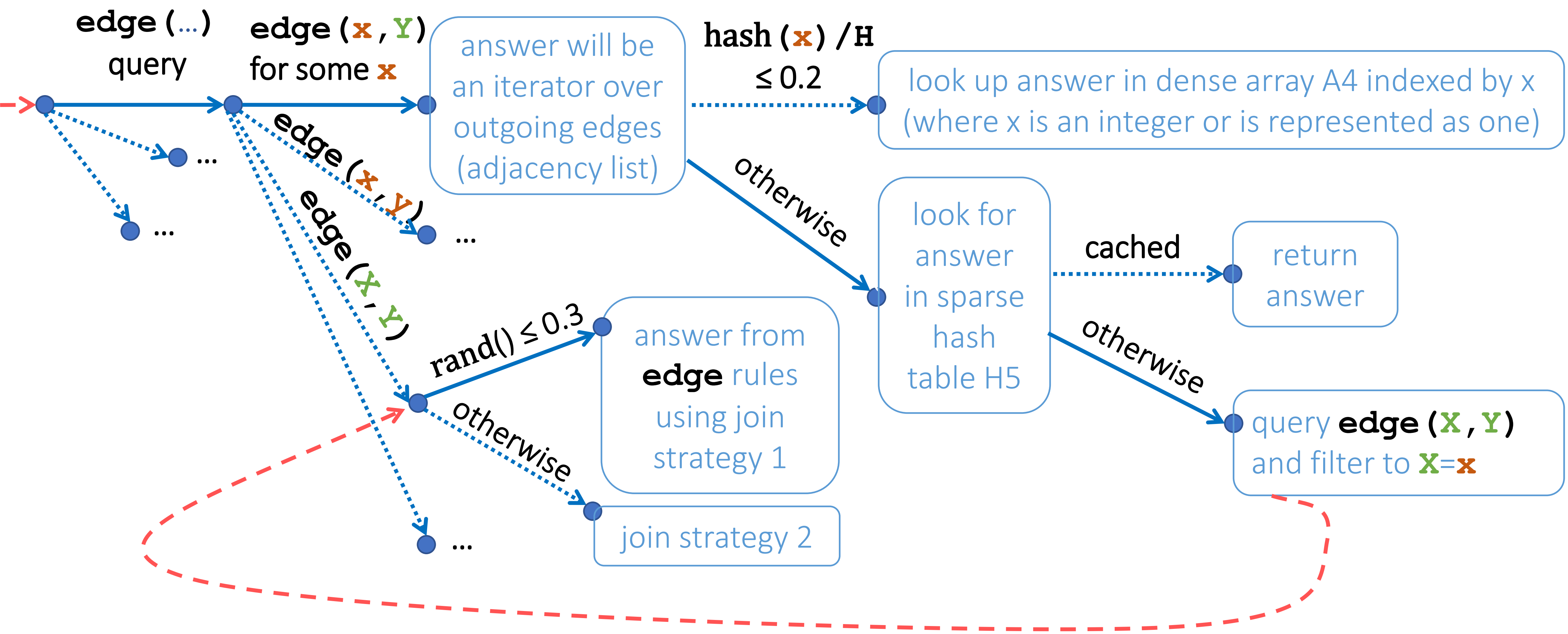

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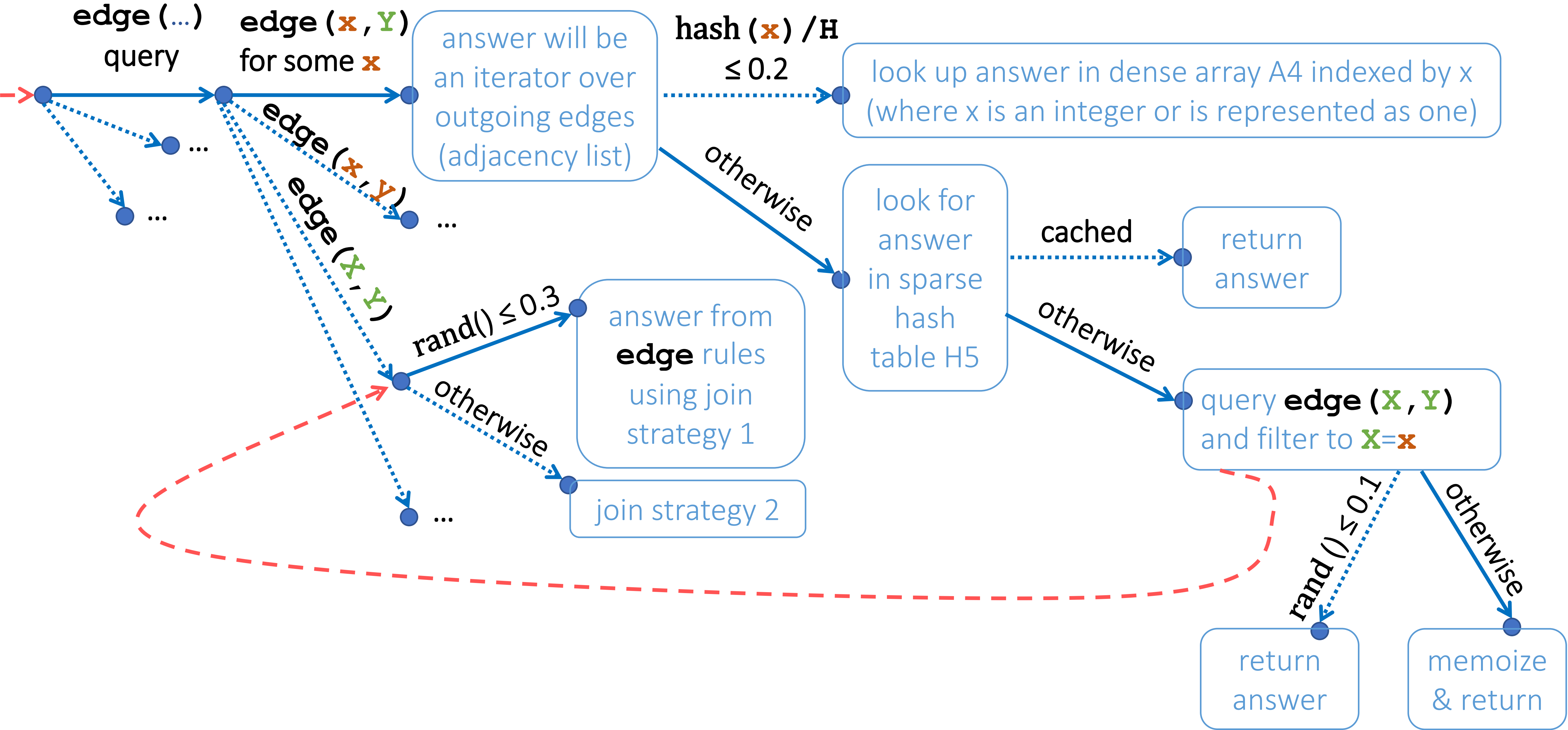

edge(…) query

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rand() ≤ 0.1

return answer

otherwise

memoize & return

edge(**x**,**y**)

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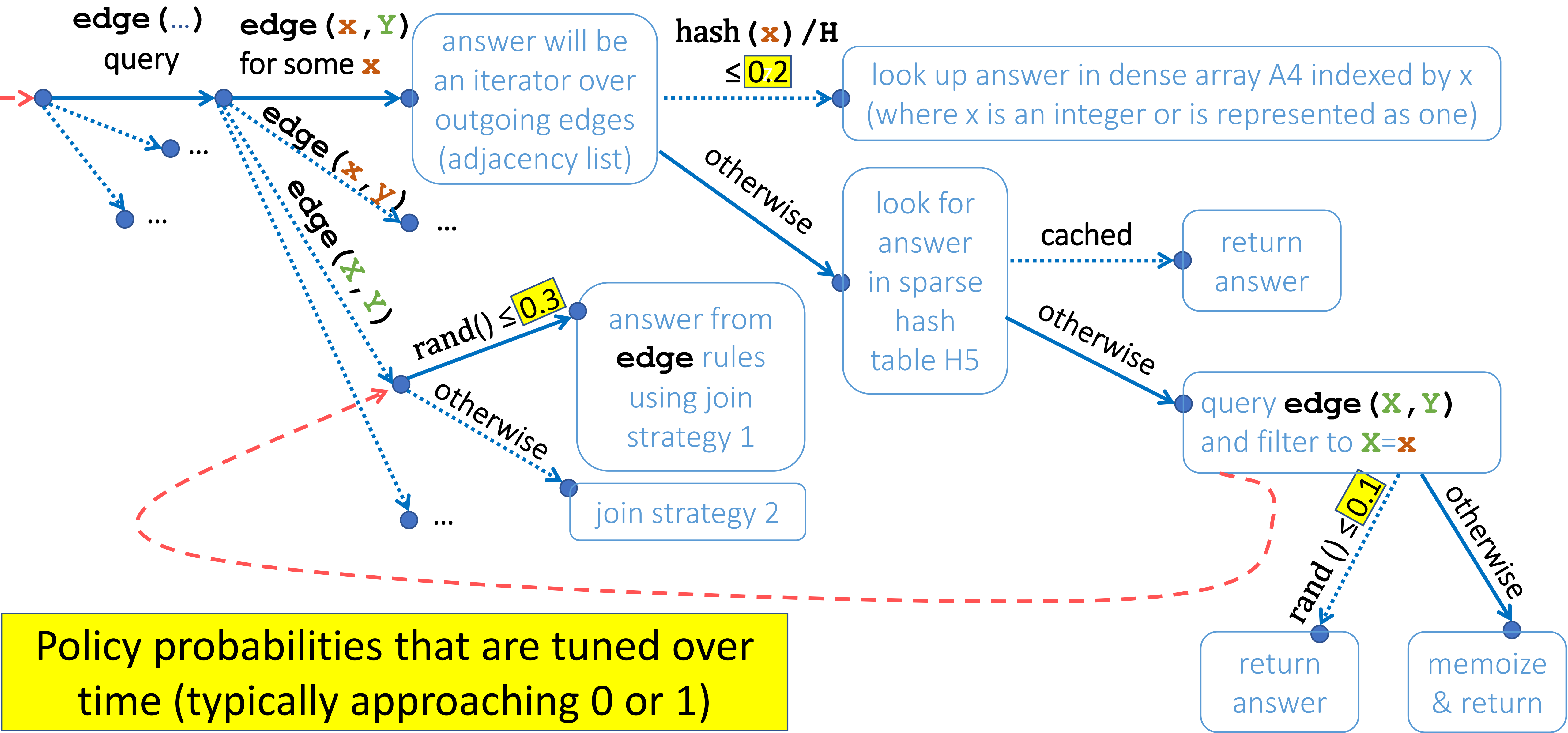

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Policy probabilities that are tuned over time (typically approaching 0 or 1)

Policy probabilities can be sensitive to context of task

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Stochastically conditioned on the following information (features).

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- **Cache characteristics**
  - Statistics: number, hit rate, frequency, & recency of memos (broken down by type)

Tuning probabilities

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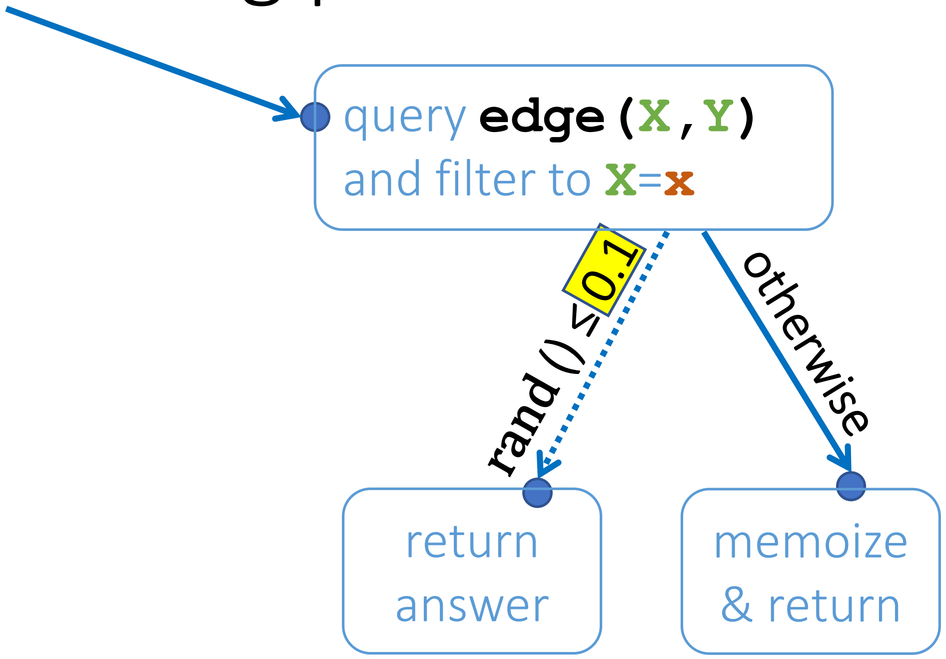

query **`edge(X,Y)`** and filter to `X`=`x`

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memoize & return

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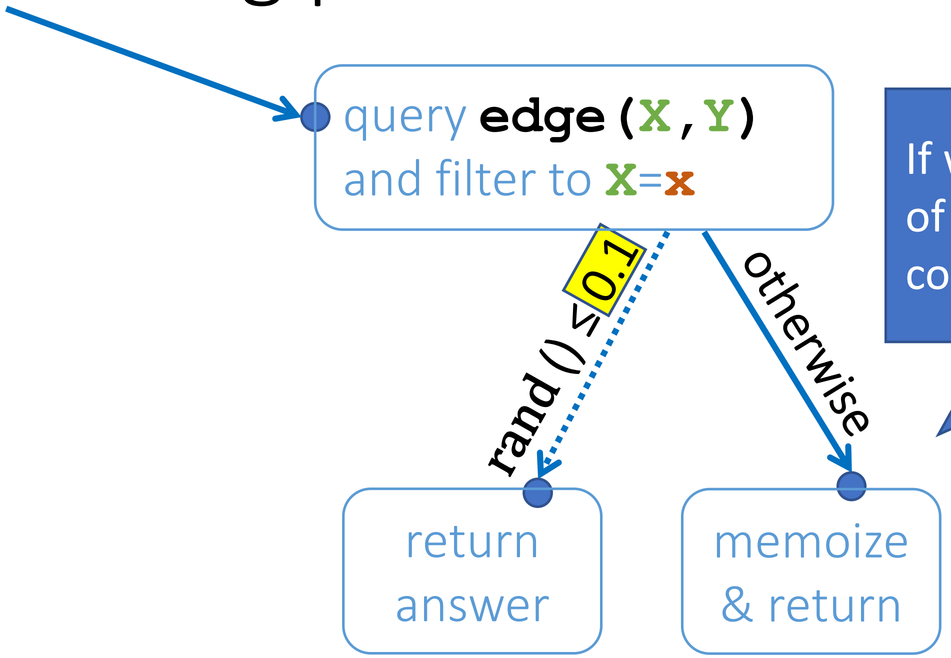
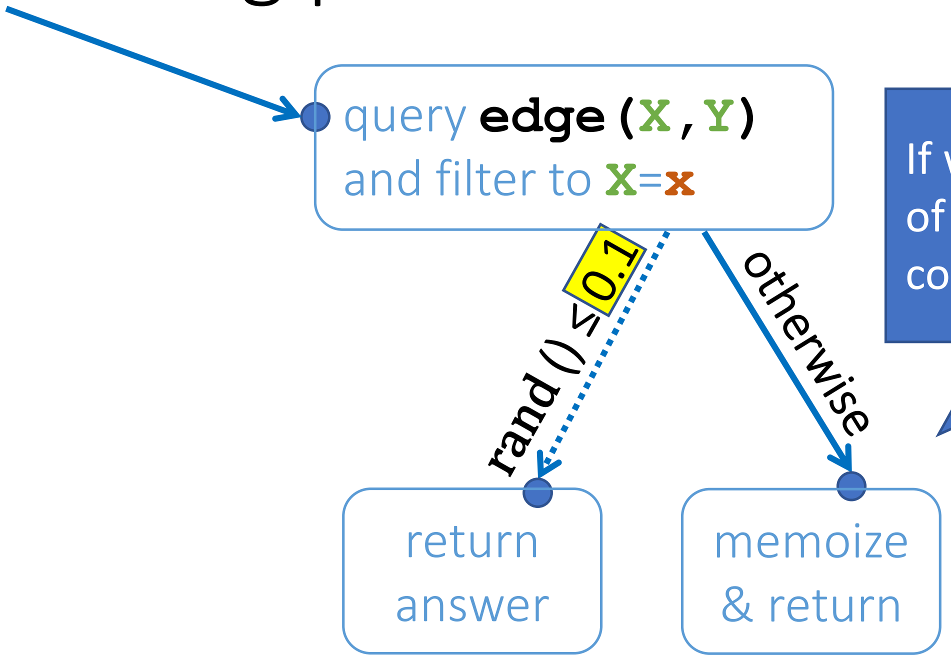


If we knew the *long-term* cost of each action in context, we could update the policy now!

Tuning probabilities



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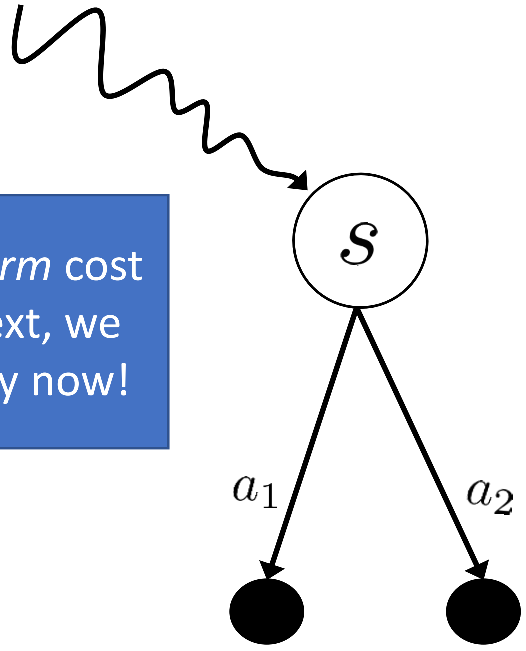

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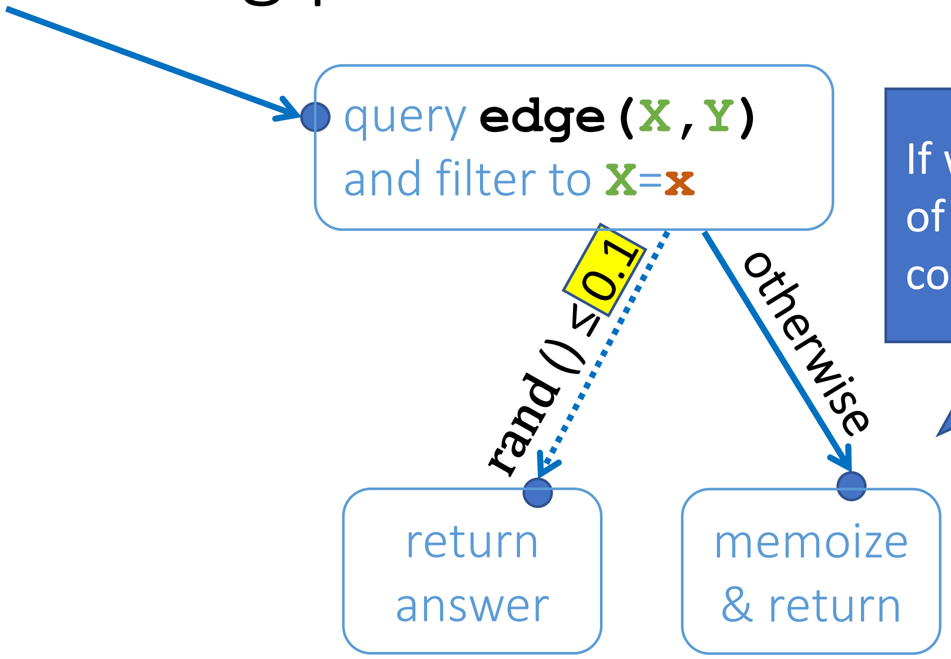

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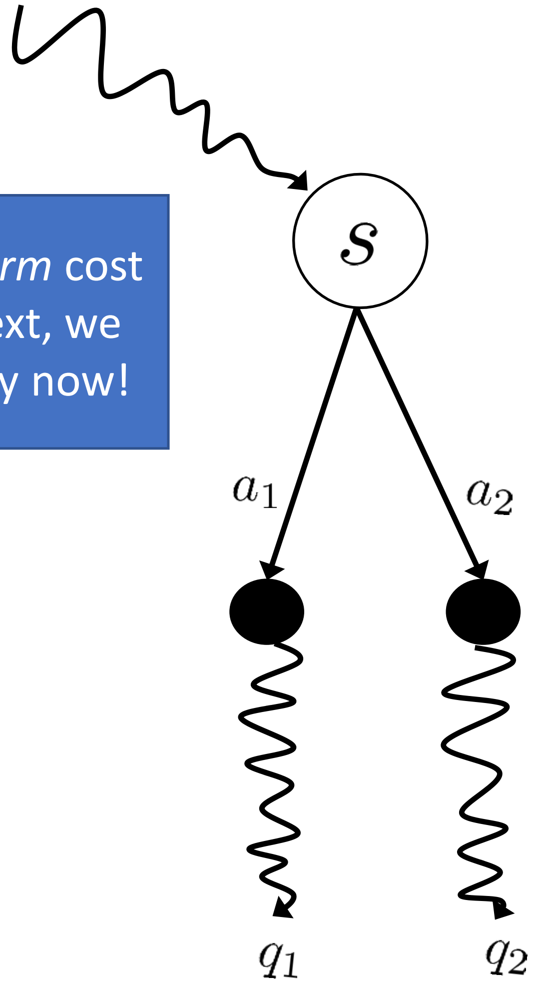
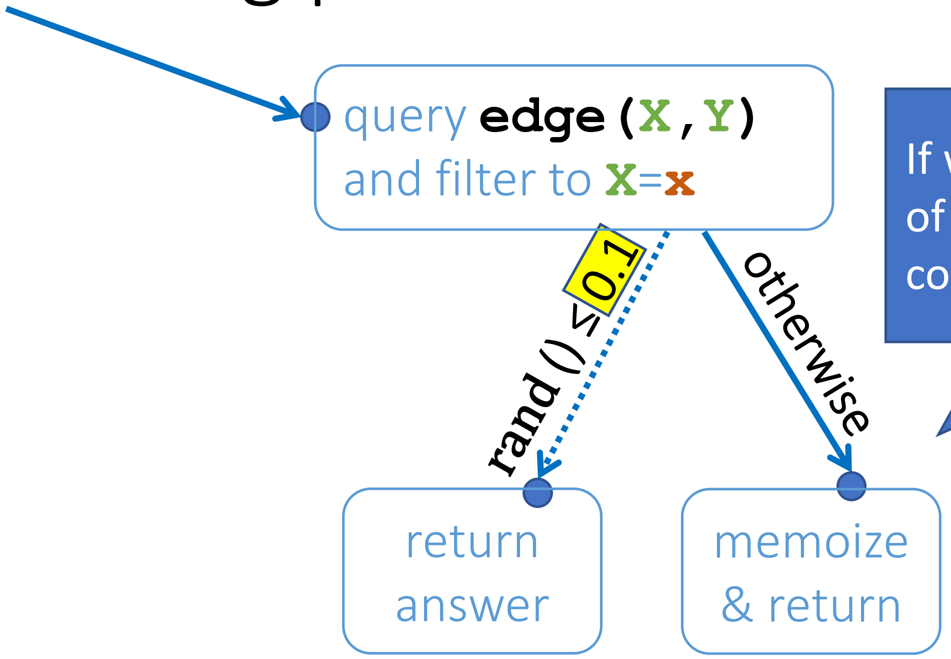


hypothetically, fork state
and run finish workload

Tuning probabilities



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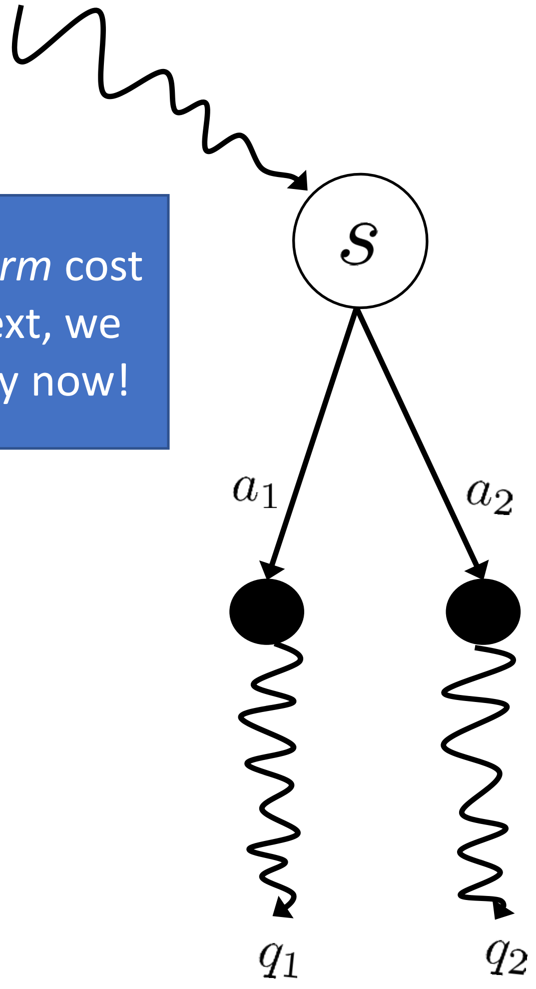

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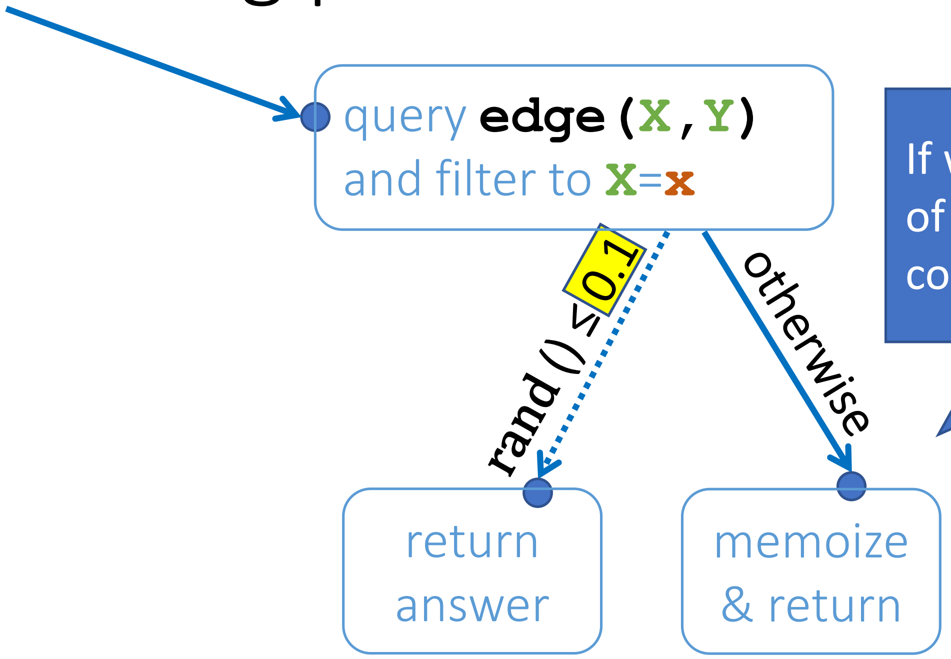
Slow!

Tuning probabilities



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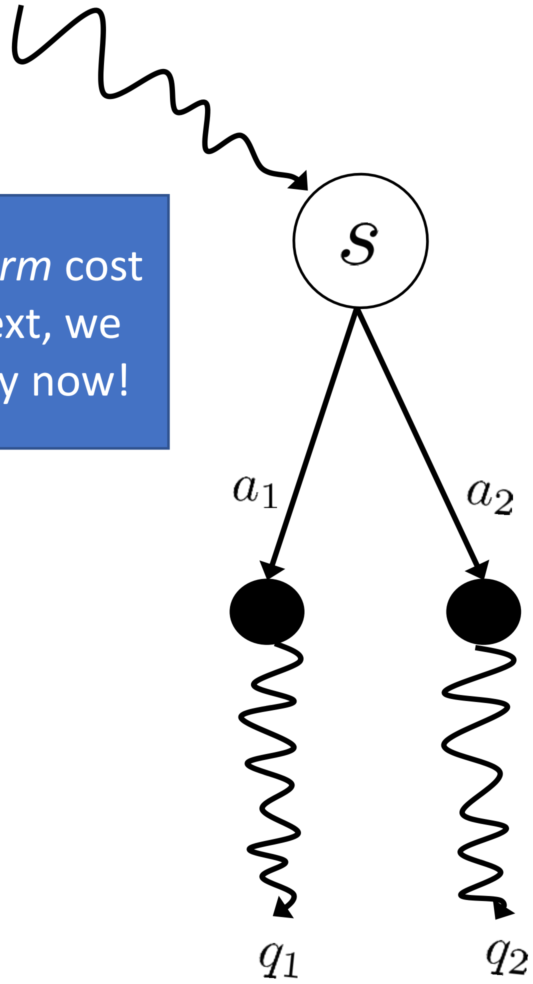

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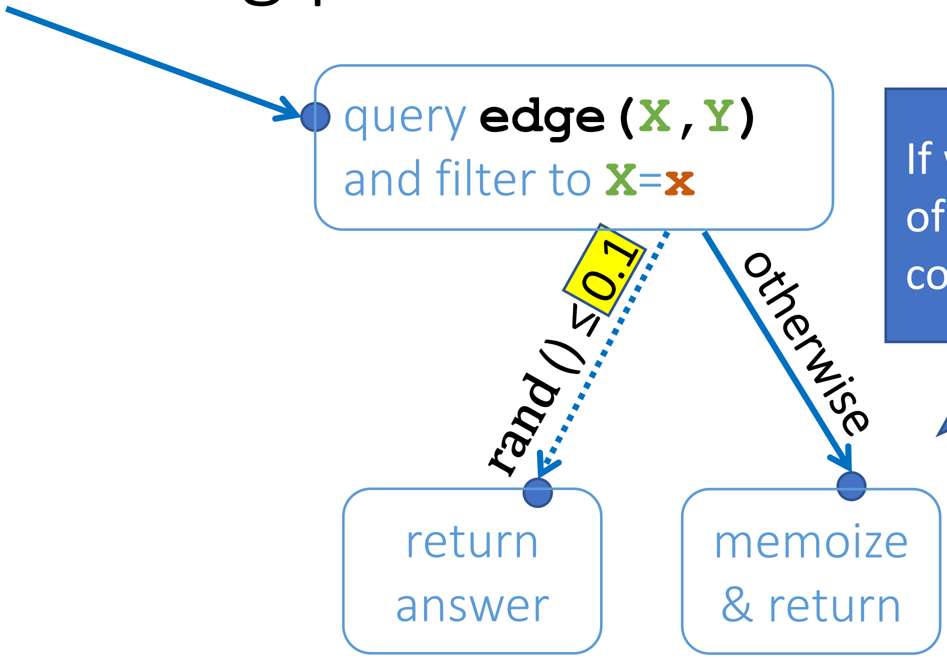
Slow!

Use ML to predict future costs!

$$\mathbb{E}\left[q_i\right] \approx \widehat{q}(s, a_i)$$

Tuning probabilities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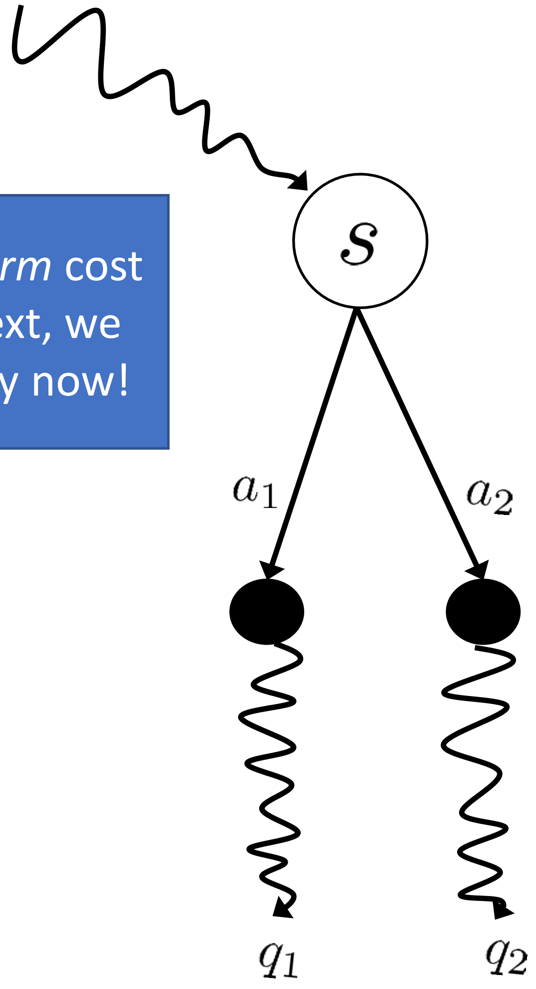

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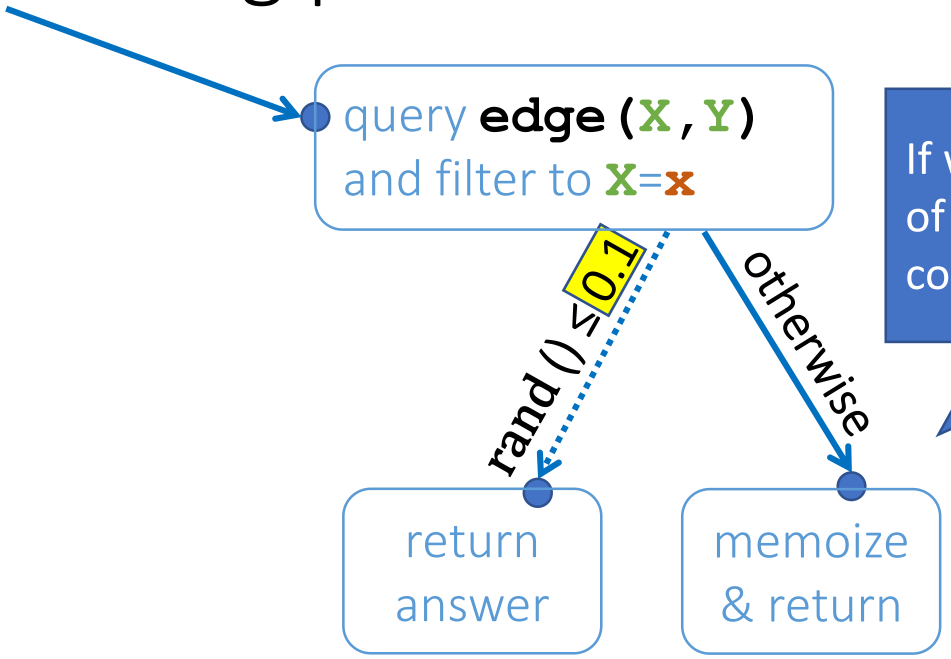

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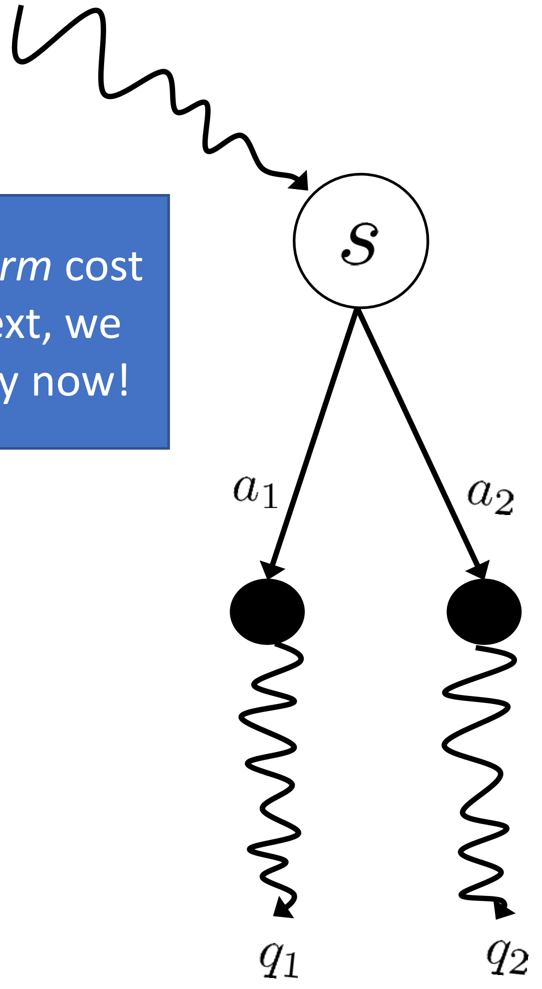

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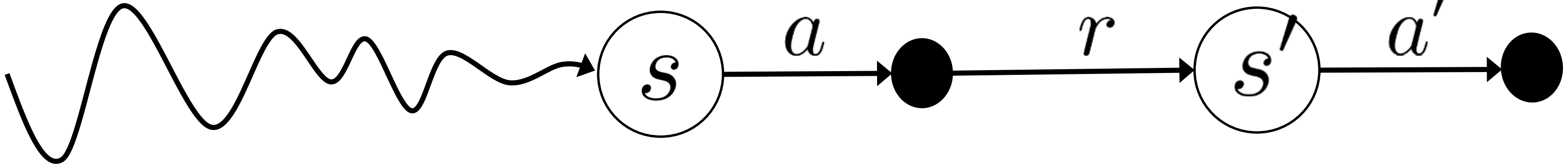
$$\mathbb{E}\left[q_i\right] \approx \widehat{q}(s, a_i) = w^\top \Phi(s, a_i)$$

Temporal difference learning



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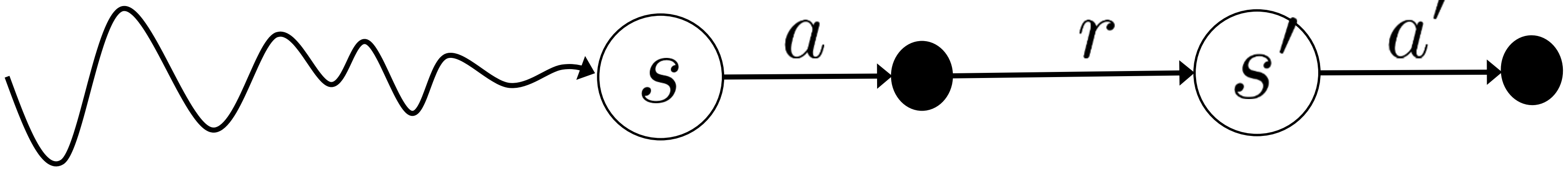

$$\widehat{q}(s,a) \approx \mathbb{E}\left[r + \widehat{q}(s',a')\right]$$

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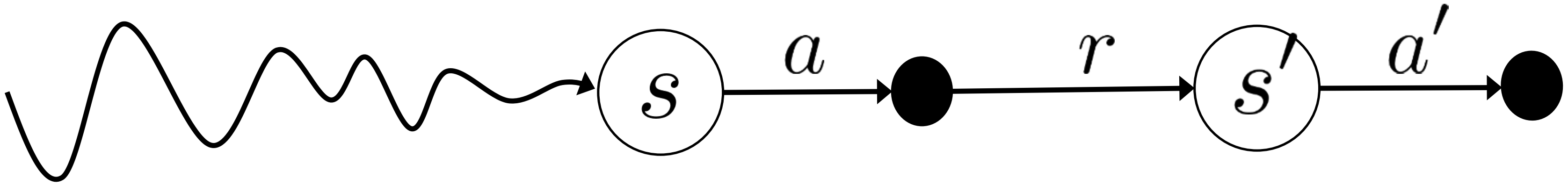

Approximate dynamic programming

$$\widehat{q}(s,a) \approx \mathbb{E}\left[r + \widehat{q}(s',a')\right]$$

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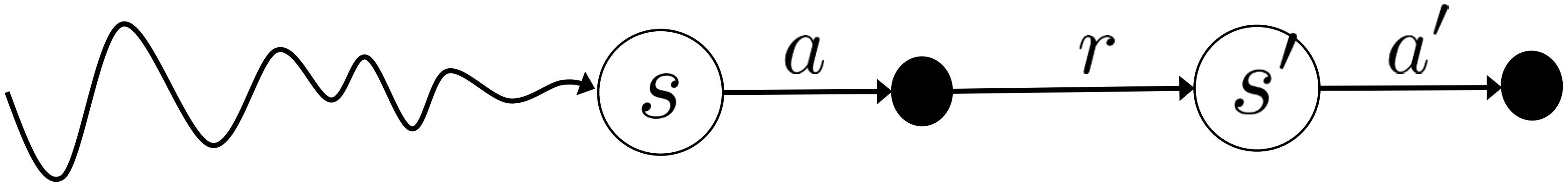

Make estimator agree with itself

Approximate dynamic programming

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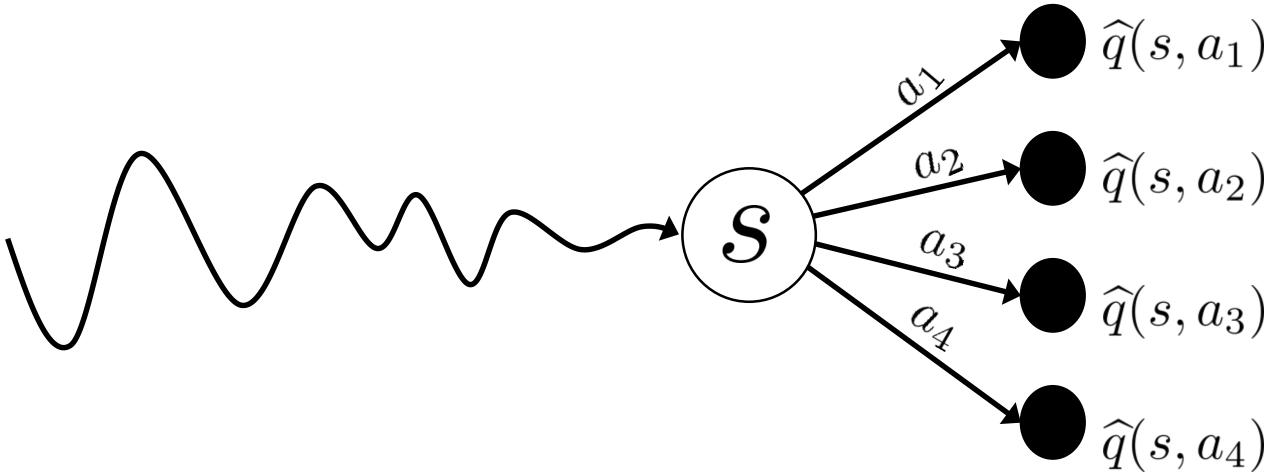
Actor-critic policy gradient



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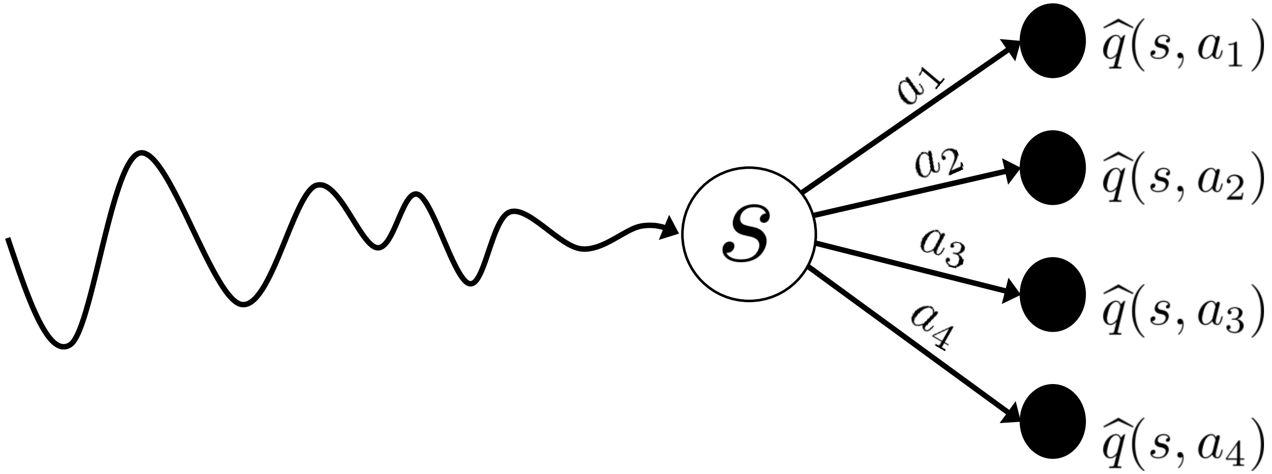

$$\pi(a|s) \propto \exp\big(\theta^\top f(s, a)\big)$$

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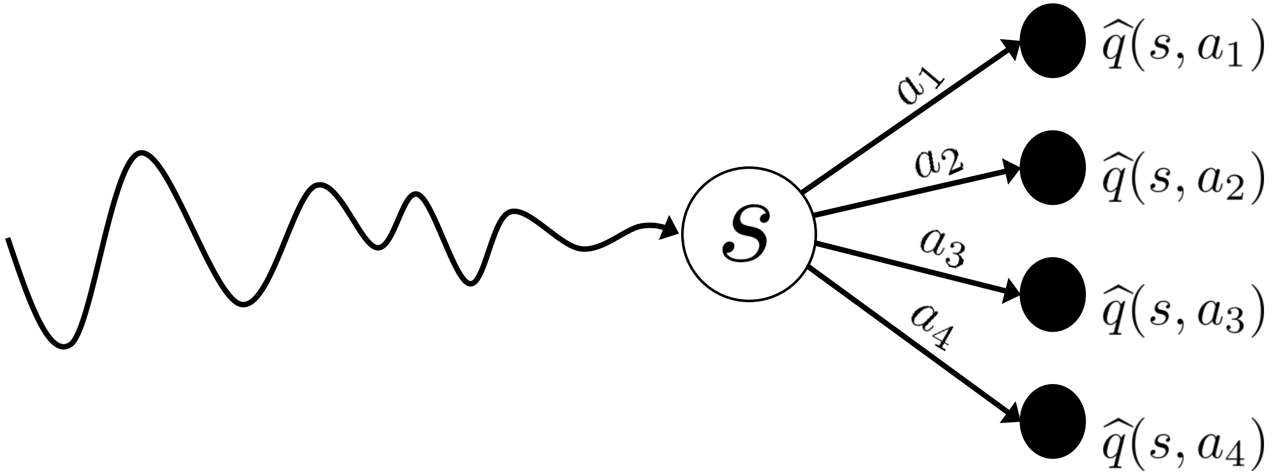
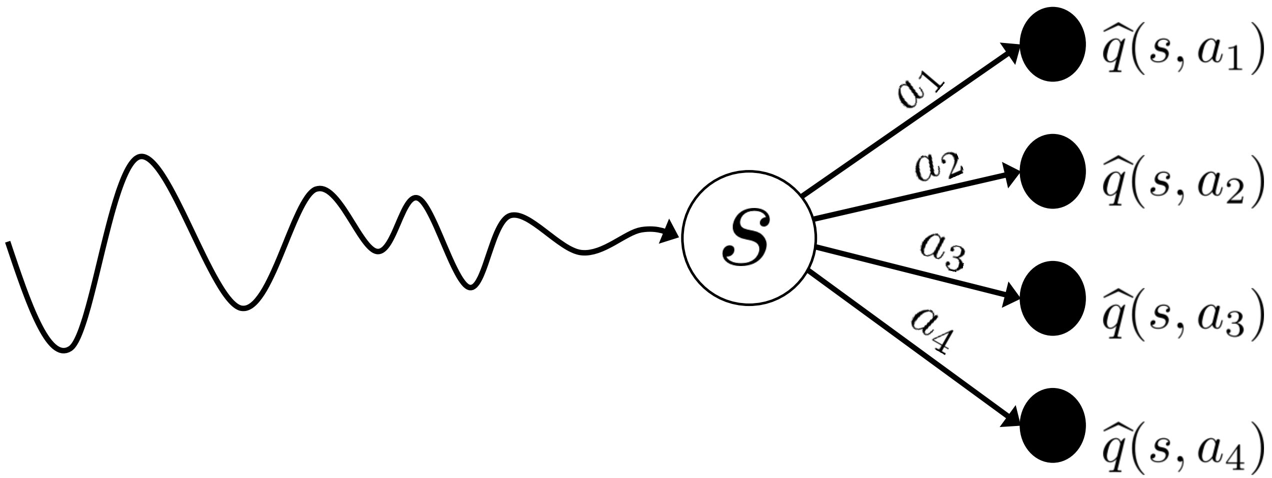


Says increase the probability of lower cost actions.

$$\pi(a|s) \propto \exp\left(\theta^\top f(s,a)\right)$$

$$\theta \leftarrow \theta - \alpha_t \cdot \widehat{q}(s,a) \nabla \log \pi(a|s)$$

Actor-critic policy gradient



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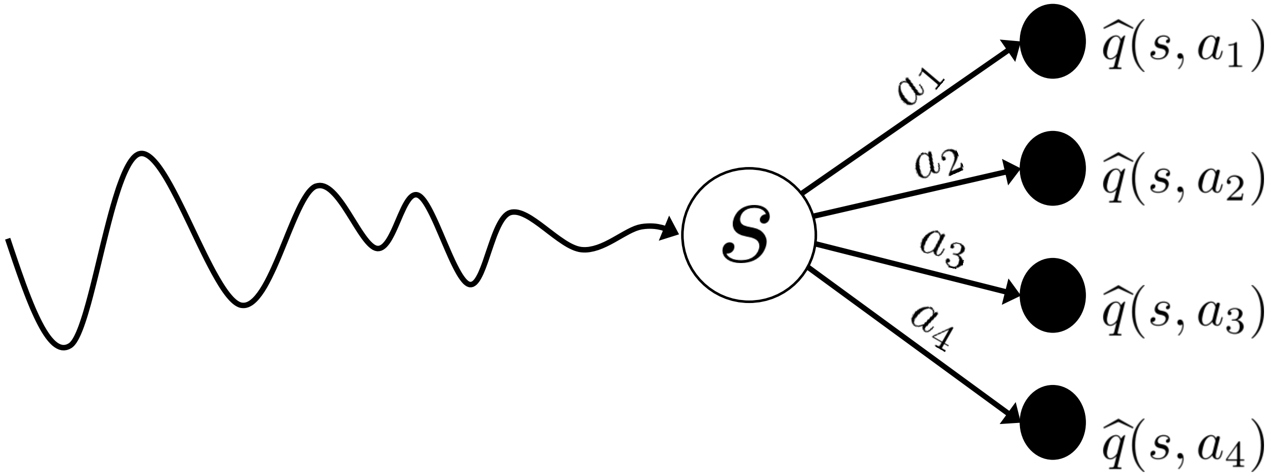

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update q

$$w = w - \beta_t \cdot (\widehat{q}(s,a) - (r + \widehat{q}(s',a'))) \cdot \Phi(s,a)$$

Summary

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- Declarative languages lend themselves to automated optimization because their solvers have a lot of freedom.

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Check out the paper! Lots of great technical details in the paper that didn't have time to get into.

State of the language

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  - Dyna 1 prototype (2005) was used in Jason’s lab, fueling a dozen NLP papers!
  - Dyna 2 prototype (2013) was used for teaching an NLP course to linguists with no programming background.
- Both were inefficient because they used too many one-size-fits-all strategies.

Thanks!

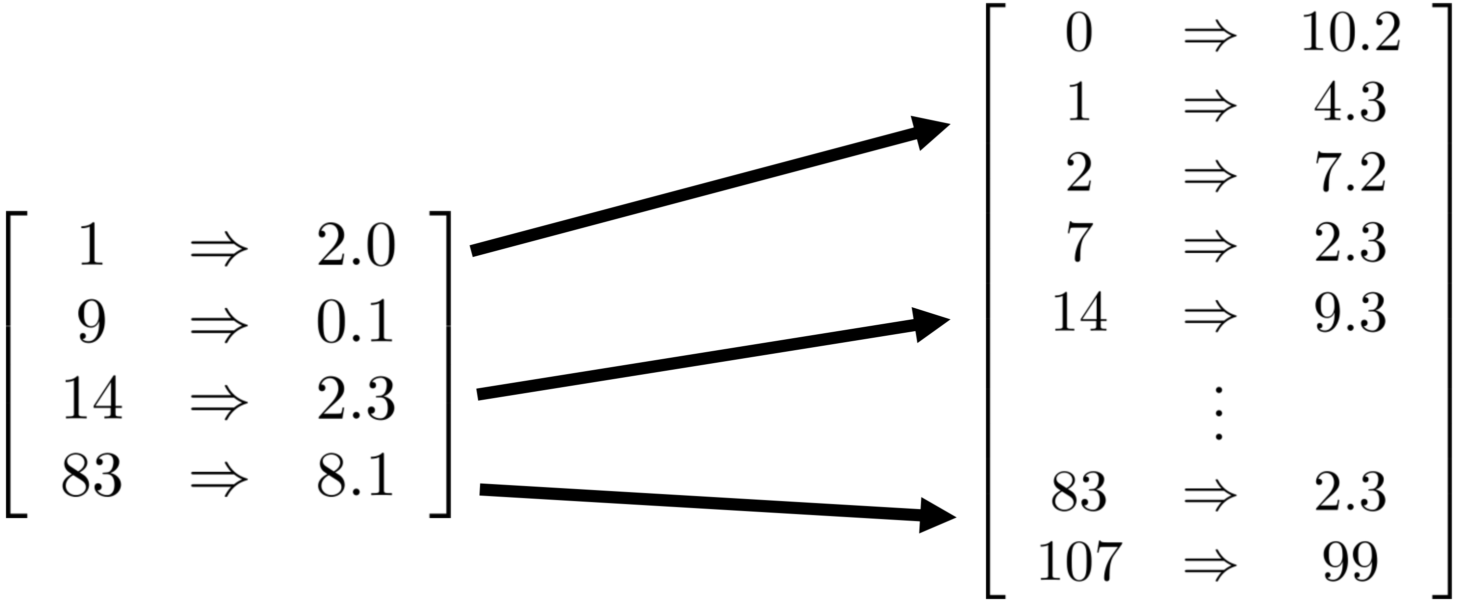
Questions? Comments?

Hire Wes Filardo!
http://cs.jhu.edu/~nwf

http://dyna.org

@xtimv
@matthewfl

Loop order, sparse vector product example



$$\begin{bmatrix} 1 & \Rightarrow & 2.0 \\ 9 & \Rightarrow & 0.1 \\ 14 & \Rightarrow & 2.3 \\ 83 & \Rightarrow & 8.1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & \Rightarrow & 10.2 \\ 1 & \Rightarrow & 4.3 \\ 2 & \Rightarrow & 7.2 \\ 7 & \Rightarrow & 2.3 \\ 14 & \Rightarrow & 9.3 \\ & \vdots & \\ 83 & \Rightarrow & 2.3 \\ 107 & \Rightarrow & 99 \end{bmatrix}$$

Join strategies

- Outer loop on `b(J,4)`, inner loop `a(I,J)`
- Outer loop on `a(I,J)`, inner loop `b(J,K)`, filter `K==4`
- Sort `a` and `b` on `J` and use Baeza-Yates intersection
- What if we can't loop over `b`? e.g.,
  `b(I,K) = X*Y.`
- In natural language parsing with the CKY algorithm, an unexpected loop order turned out to be 7-9x faster than the loop order presented in most textbooks because of cache locality (Dunlop et al. 2010).

```
% matrix multiplication
c(I,K) += a(I,J) * b(J,K).
```

Memoization and data structures

- Do we store results for future use?
  (tradeoff: memos must be kept up-to-date!)
- What data structure?

Batching, answering bigger queries/updates

- Batch pending `c` queries.
- Preemptively compute a broader query, `c(I,K)`
  Use clever mat-mul alg. (sparse or dense?)

Inlining

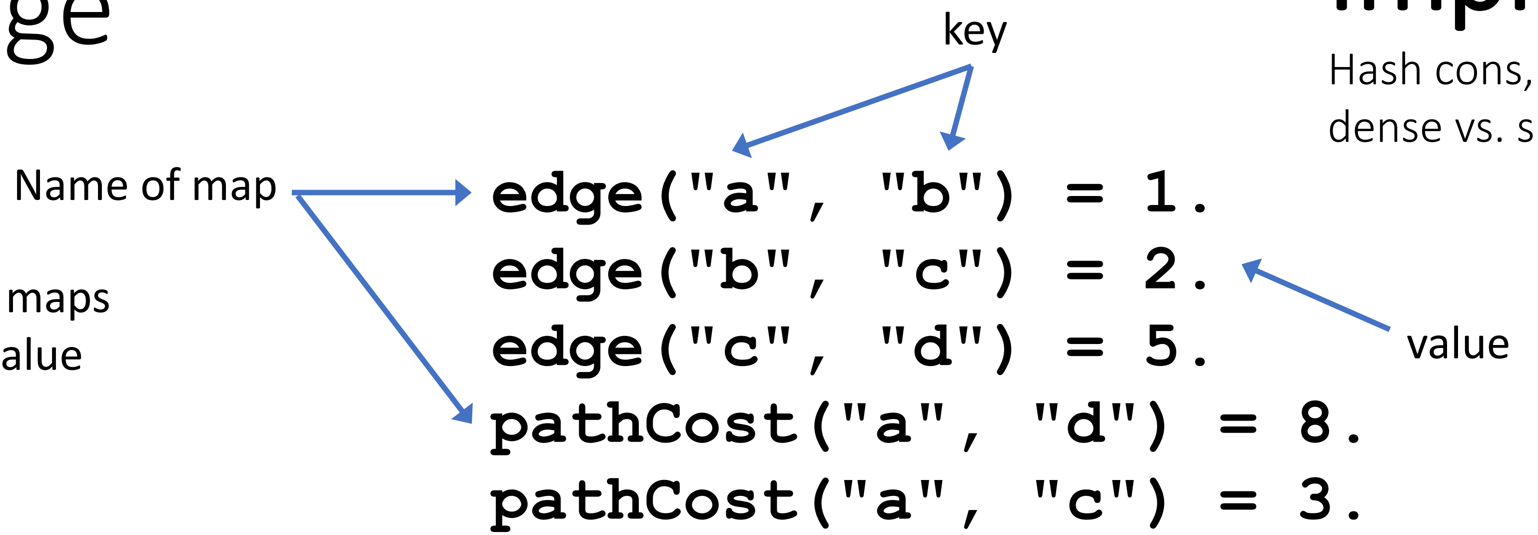
- Inline a and/or b queries.
- Bypass agenda and route directly to consumer, e.g.,
  `d(I) max= c(I,K).`
- Reduce overhead of method calls
- Reduce overhead of task indirection through agenda

Mixed policies

- Mixed task strategies selection
  - Policy will encounter similar tasks frequently
- Mixed storage strategies
  - e.g., use a hash table, prefix trie, dense array, …
  - Problem: random choice of strategy might not be consistent
    - E.g. might write to A and read from B (because of randomness)

Storage

Named maps
key -> value



```
edge("a", "b") = 1.
edge("b", "c") = 2.
edge("c", "d") = 5.
pathCost("a", "d") = 8.
pathCost("a", "c") = 3.
```

Implementations?

Hash cons, trie (different orders on keys), dense vs. sparse, sorted (what to sort on)

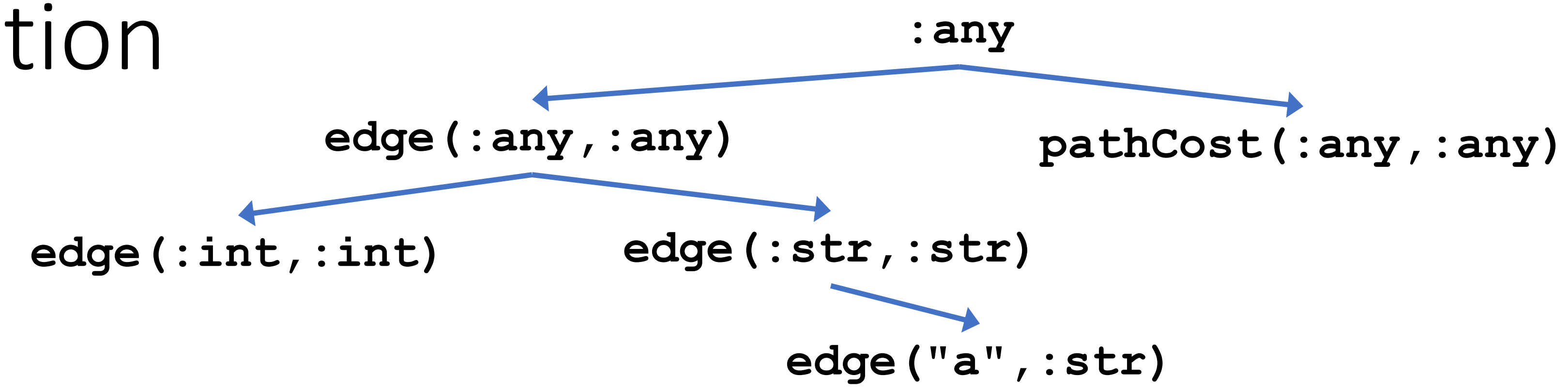
Queries

What's the weight of edge a->b	`? edge("a","b")`
Outgoing edges from a	`? edge("a",Y)`
Incoming edges to b	`? edge(X,"b")`
List all edges	`? edge(X,Y)`
List all self loops	`? edge(X,X)`
Edges with weight >= 10	`? edge(X,Y) >= 10`

Efficiency depends on

- Frequency of different queries
- Overhead of read/writes
- Sizes
- Lower-level thresholds

Mixed storage solution



`:any`

`edge(:any,:any)`

`pathCost(:any,:any)`

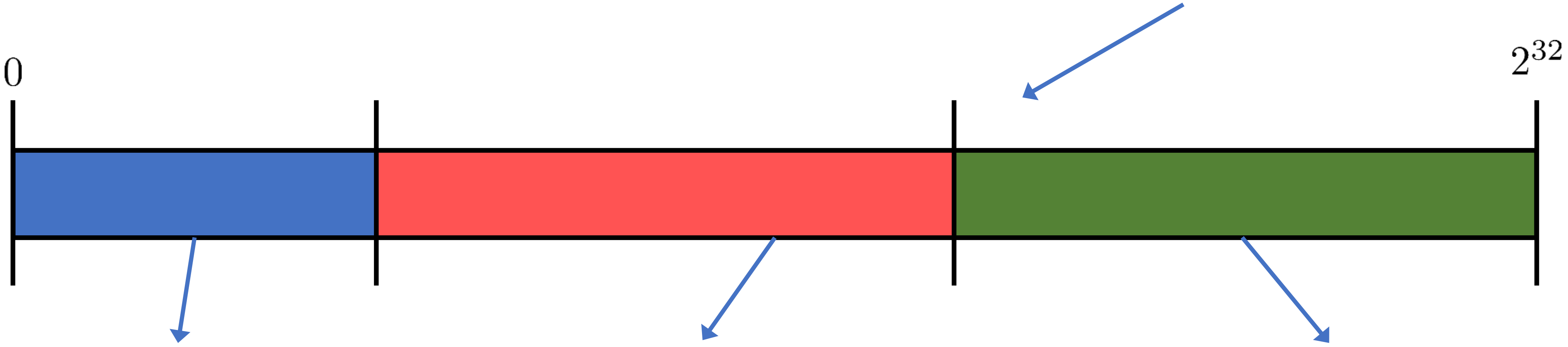
`edge(:int,:int)`

`edge(:str,:str)`

`edge("a",:str)`

hash(`edge("a", "b")`) / 2^32 ~ Uniform(0,1)

Small, temporary
data duplication

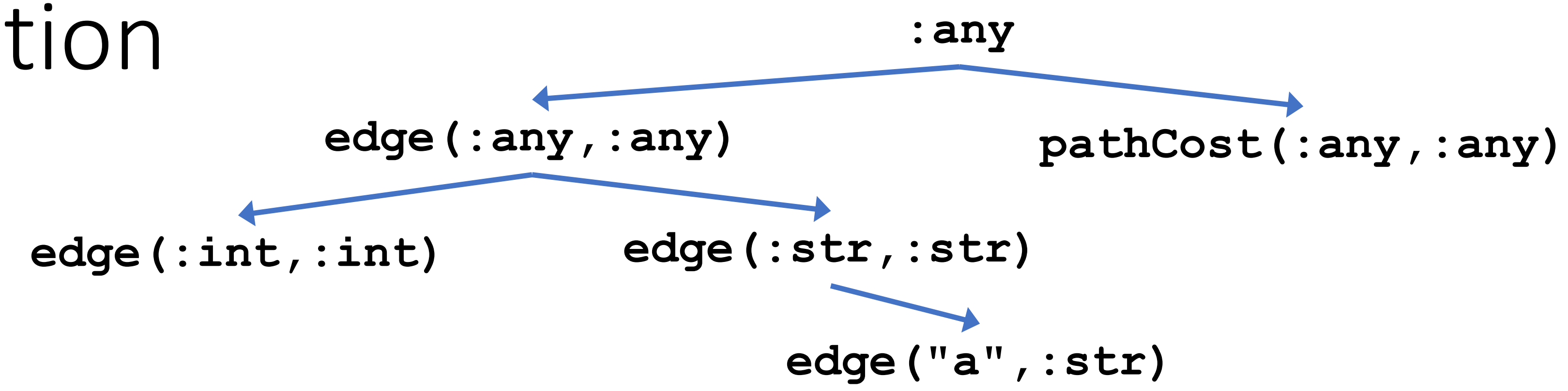


Hash table

Trie 1->2

Trie 2->1

Mixed storage solution



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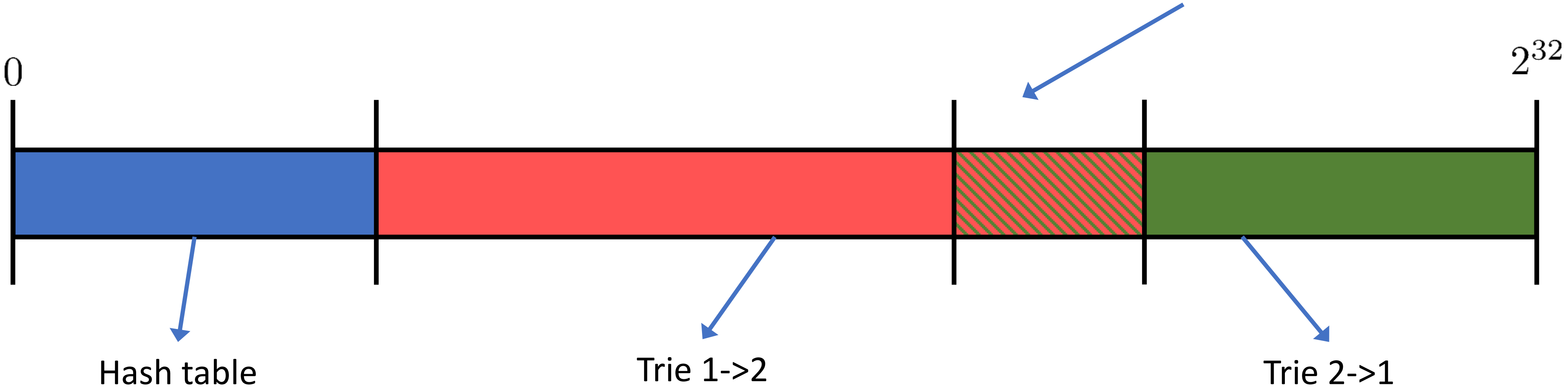
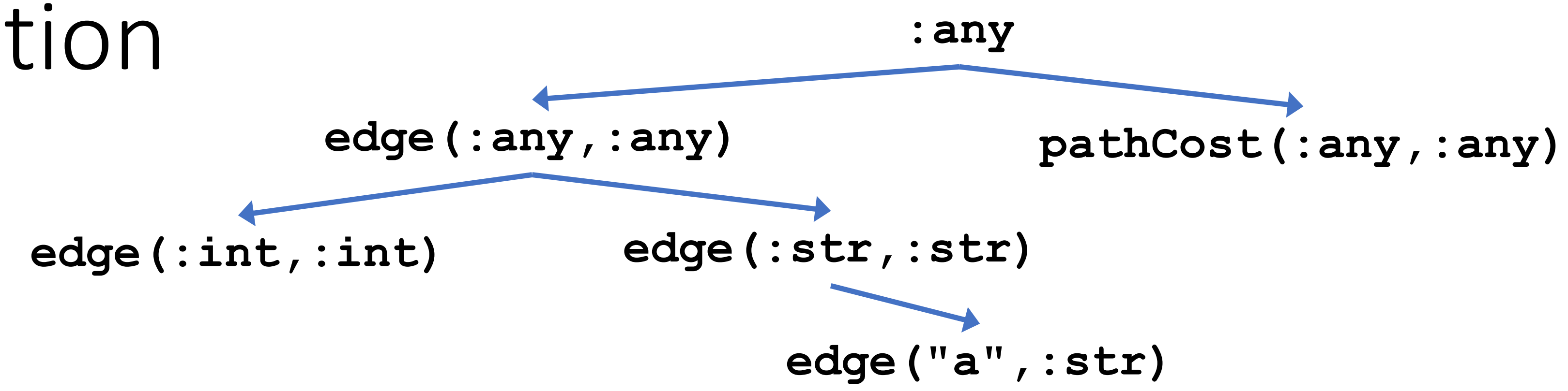


Small, temporary data duplication

Mixed storage solution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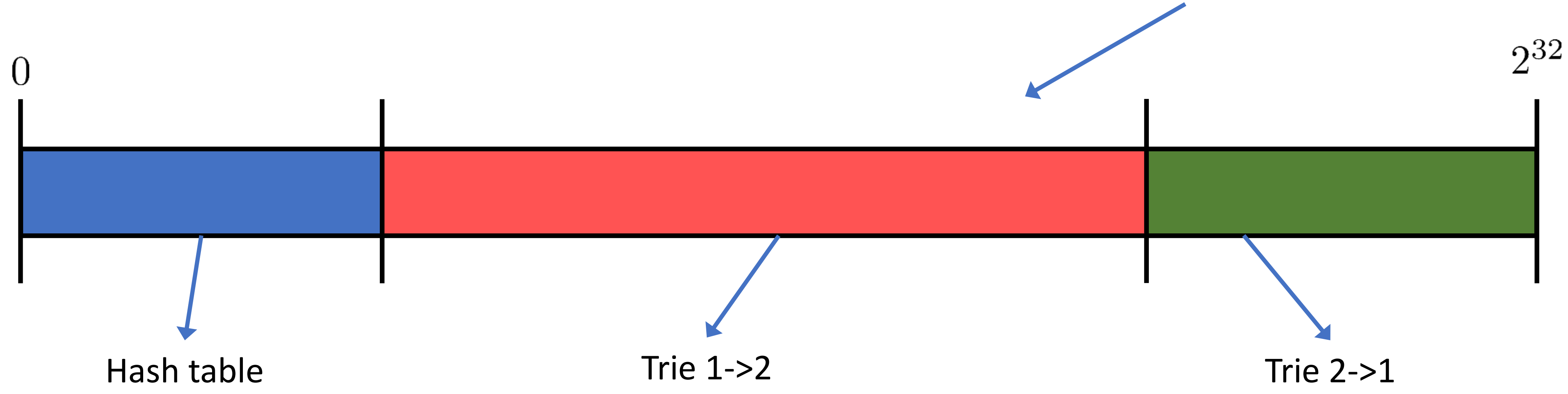
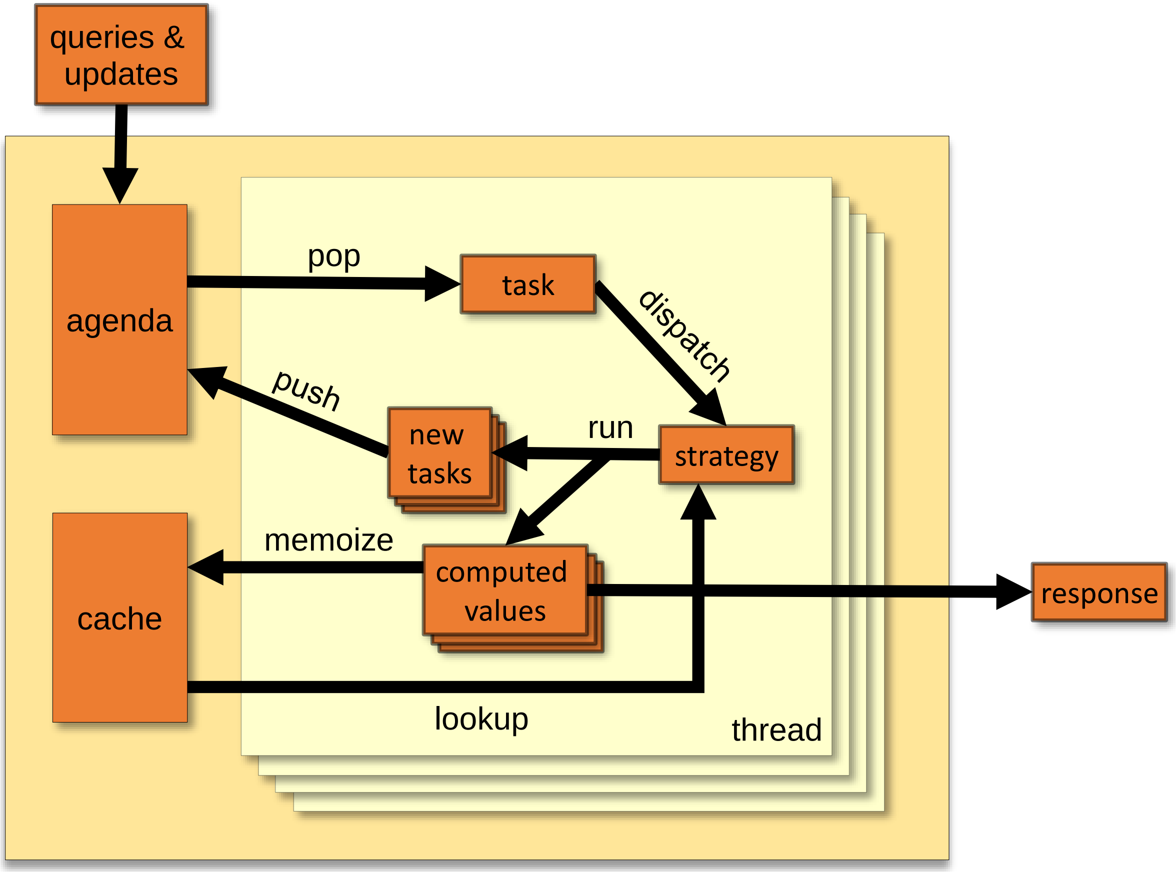
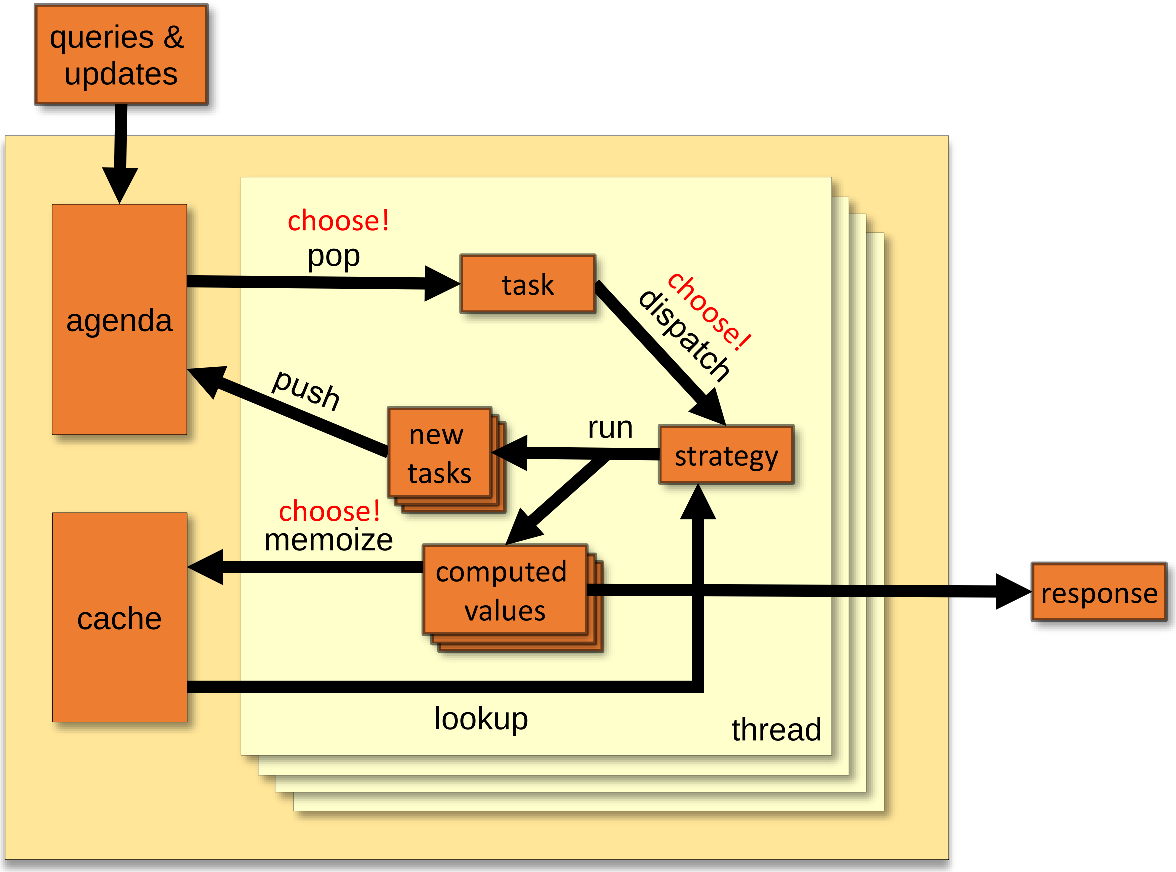


Small, temporary data duplication

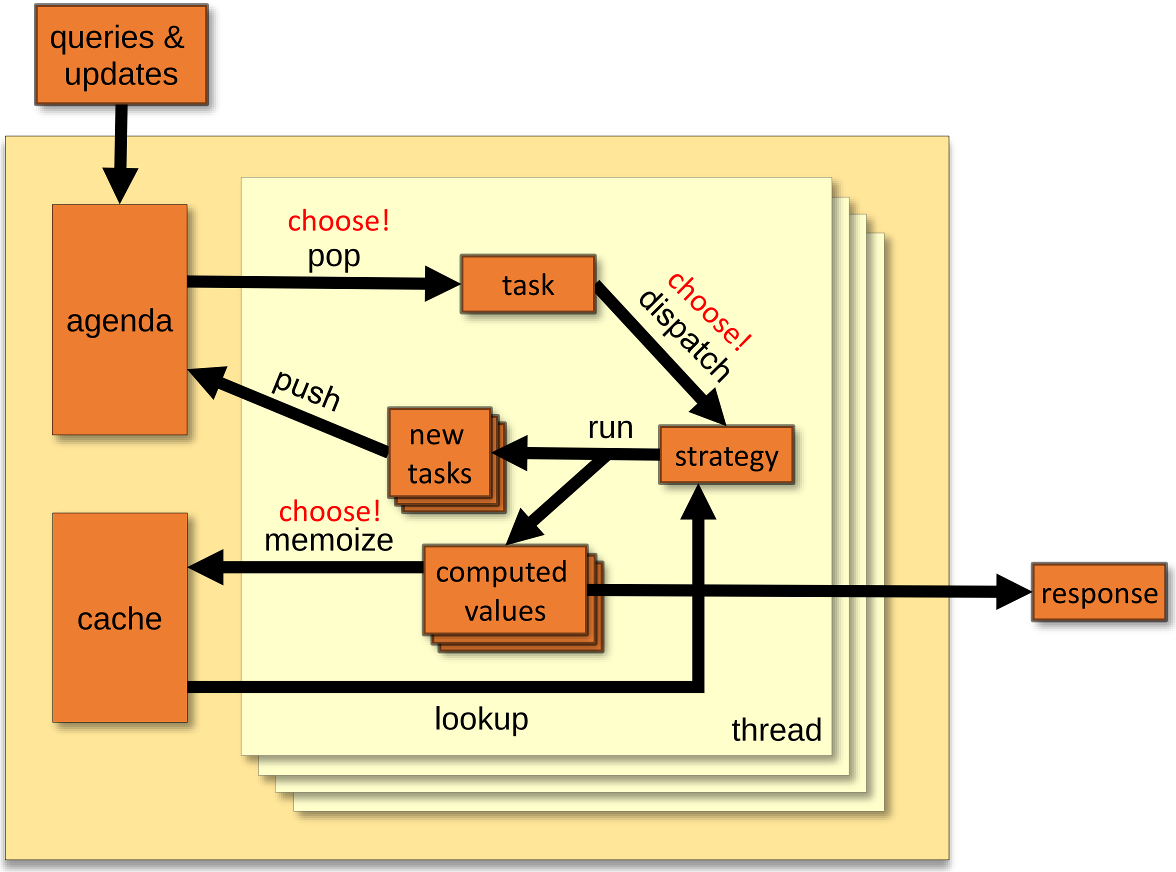
Learning to choose a good strategy



Learning to choose a good strategy

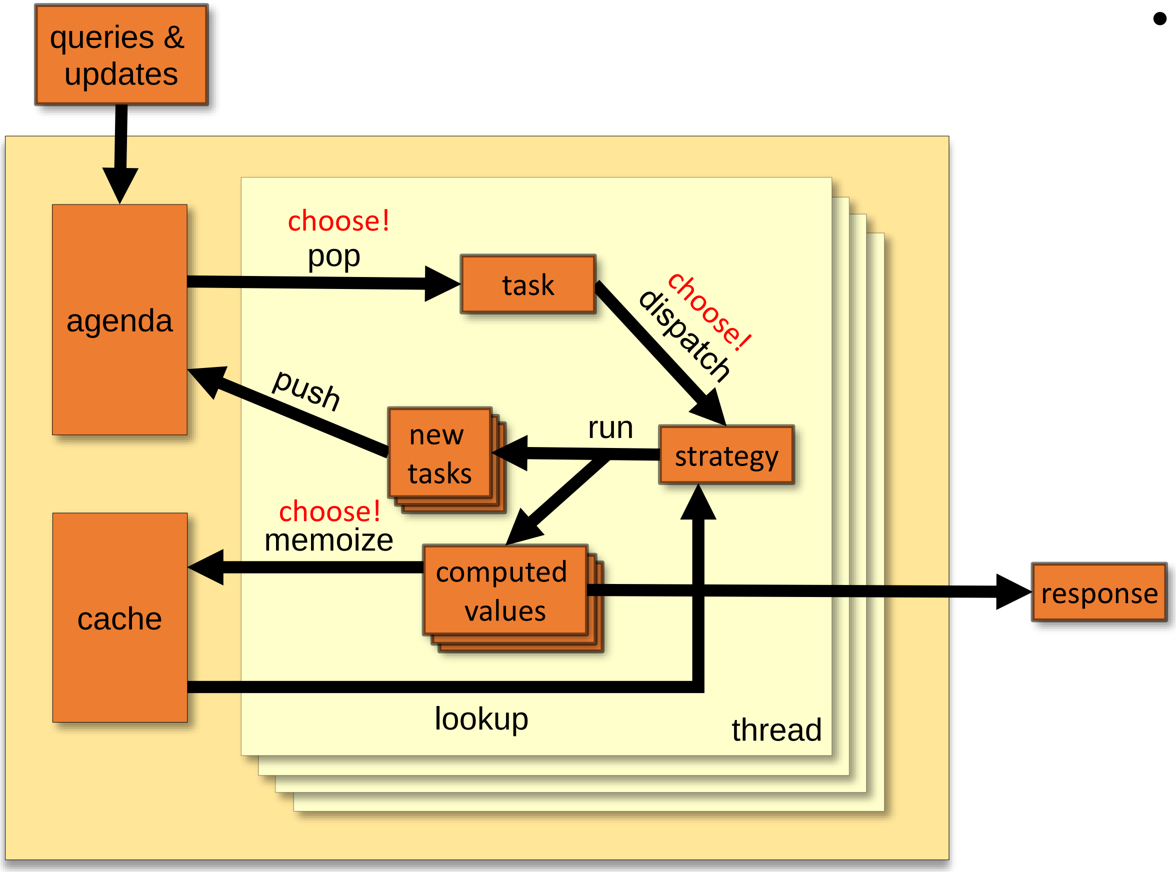


Learning to choose a good strategy



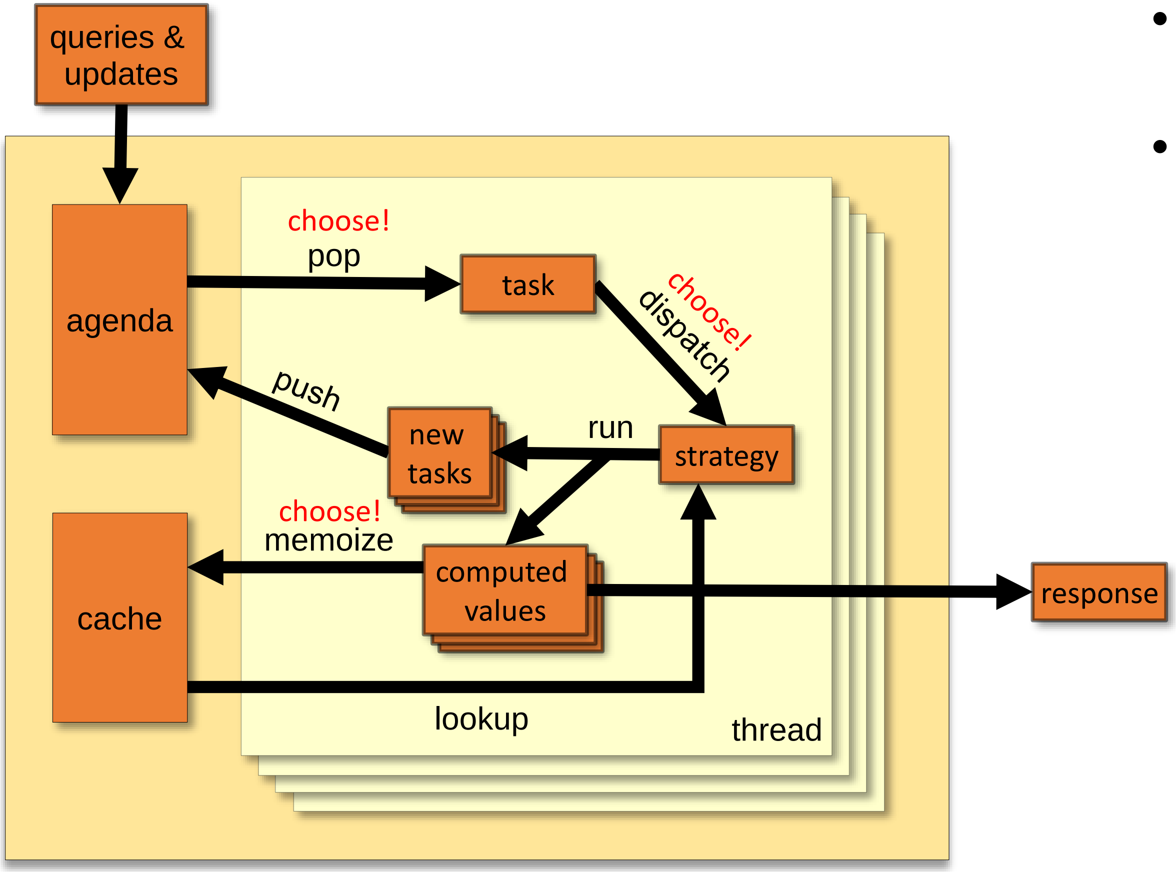
1. **Bandit**: Each time we execute a task (e.g., compute `c(I,j)` for an argument `j`):

Learning to choose a good strategy



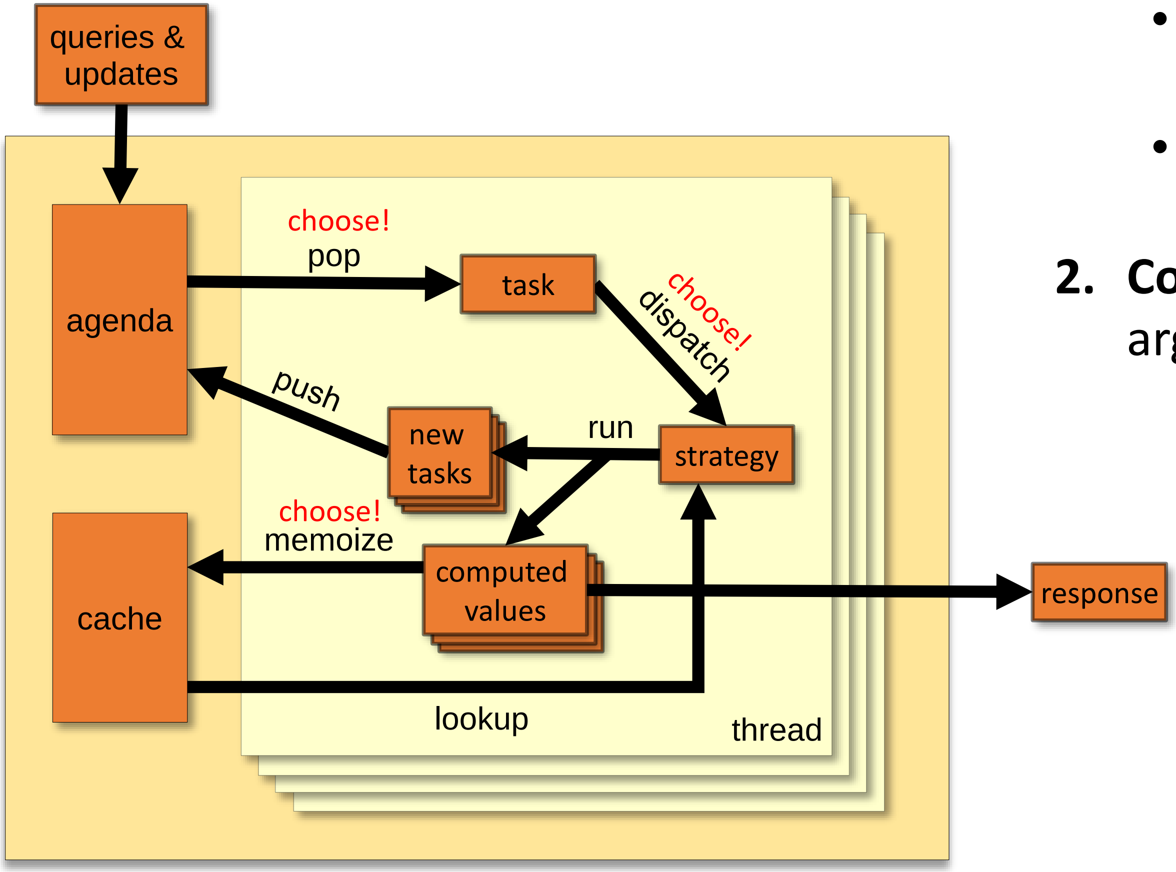
1. **Bandit**: Each time we execute a task (e.g., compute `c(I,j)` for an argument `j`):
    - Randomly try one of the available strategies (explore) according to some probability distribution

Learning to choose a good strategy



1. **Bandit**: Each time we execute a task (e.g., compute `c(I,j)` for an argument `j`):
   - Randomly try one of the available strategies (explore) according to some probability distribution
   - Bias this distribution in favor of strategies with lower measured cost (exploit).

Learning to choose a good strategy



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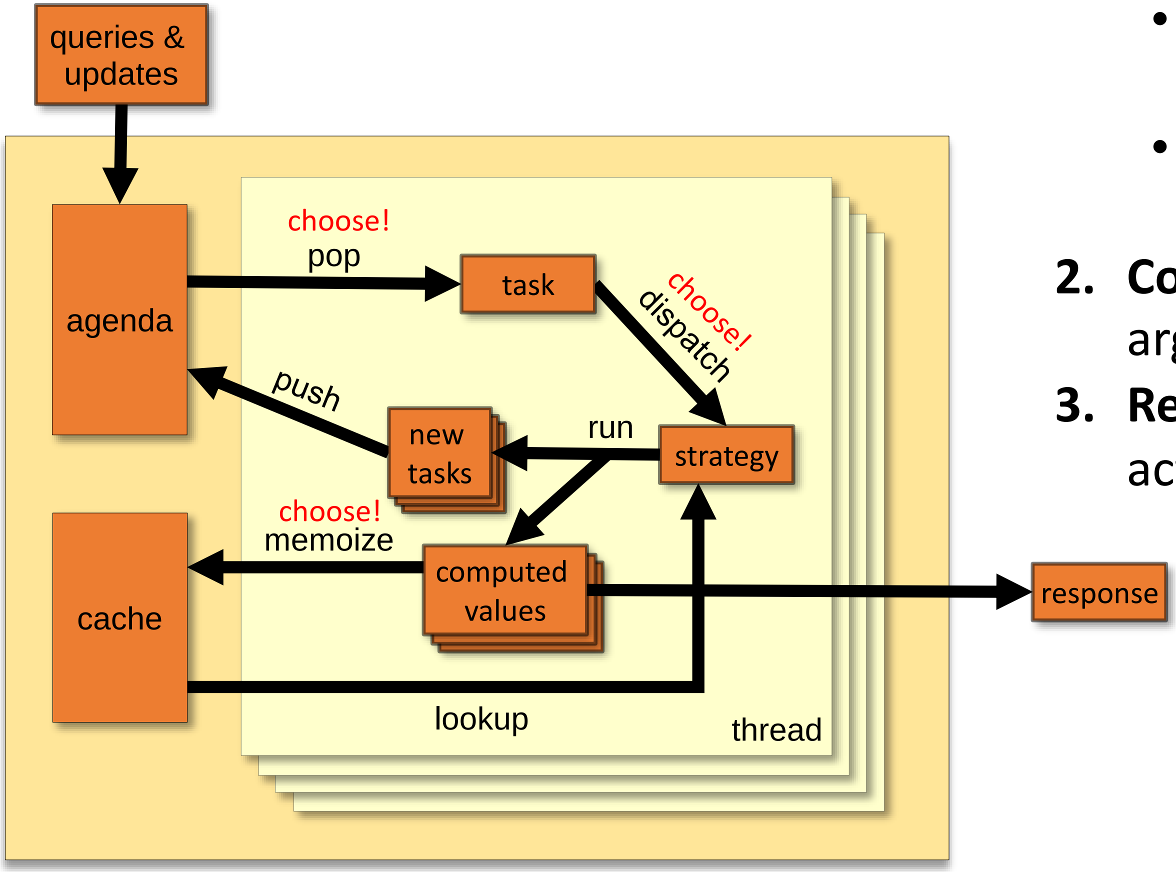
2. **Contextual bandit**: Allows distribution to depend on task arguments (e.g., `j`) and solver state.

Learning to choose a good strategy



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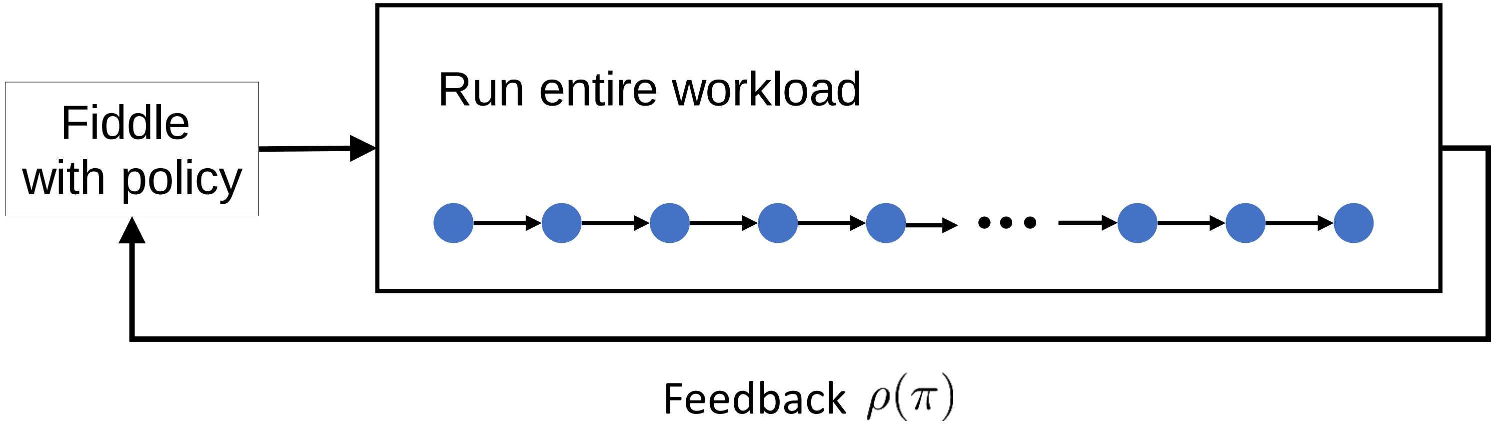
2. **Contextual bandit**: Allows distribution to depend on task arguments (e.g., `j`) and solver state.
3. **Reinforcement learning**: Accounts for *delayed* costs of actions.

Back to online training…

Back to online training…



Fiddle with policy

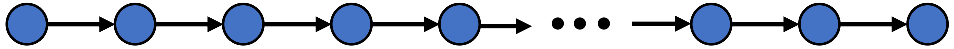
Run entire workload

Feedback $\rho(\pi)$

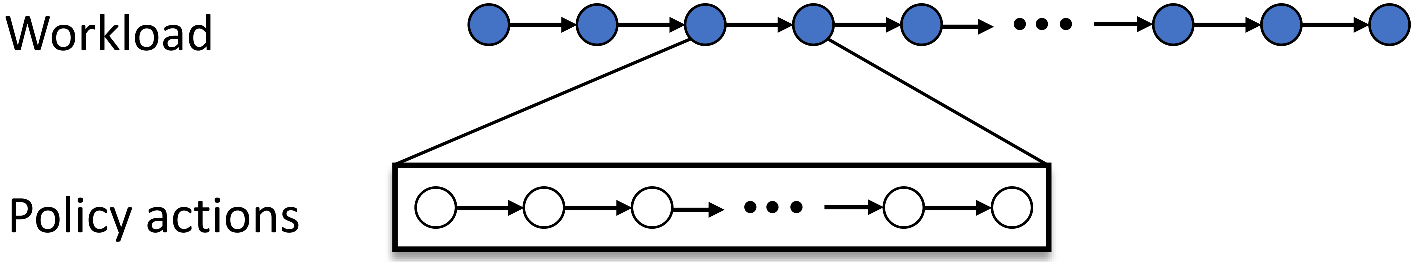
Solver Actions

Solver Actions

Workload



Solver Actions



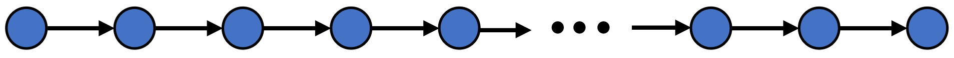
Rewrite the objective function

TODO inline in parens
use underbrace to give it a name

Add Jason integral picture?

Rewrite the objective function

Workload *i*



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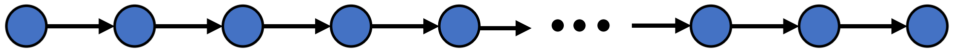

$$\rho(\pi) = \mathbb{E}\left[\sum_{i=1}^{\infty} \gamma^i \lambda_i \,\mathrm{latency}(i)\right]$$

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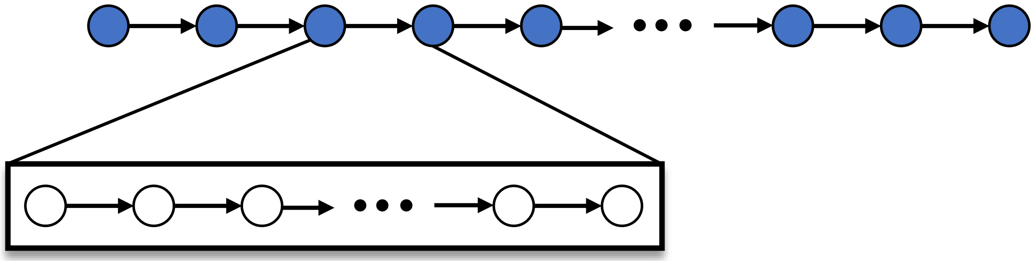

Workload *i*

Actions *t*

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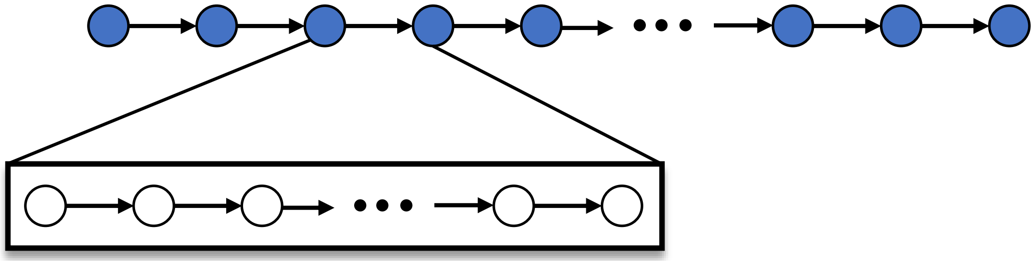

Workload *i*

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$$\rho(\pi) = \mathbb{E}\left[\sum_{i=1}^{\infty} \gamma^i \lambda_i \,\mathrm{latency}(i)\right]$$

$$= \mathbb{E}\left[\sum_{t=1}^{\infty} \mathrm{load}(t) \cdot (\mathrm{clock}(t+1) - \mathrm{clock}(t))\right]$$

Rewrite in terms of the policy's time scale (used in RL)

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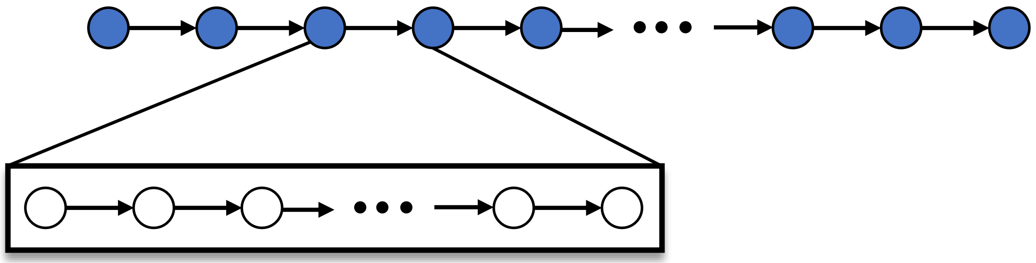
Rewrite the objective function



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Rewrite in terms of the
policy's time scale (used in RL)

Each step tries to
decrease the load

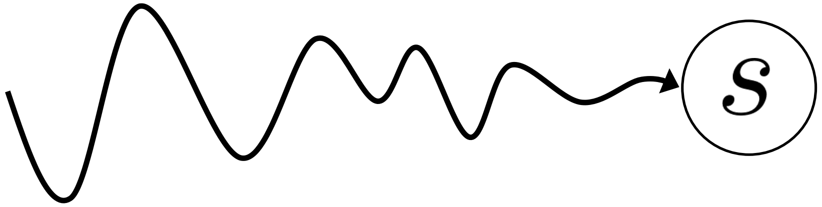
$$\mathrm{load}(t) = \sum_{i \in \mathcal{O}(t)} \gamma^i \lambda_i$$

TODO inline in parens
use underbrace to give it a name

Add Jason integral picture?

Life of π

Life of π



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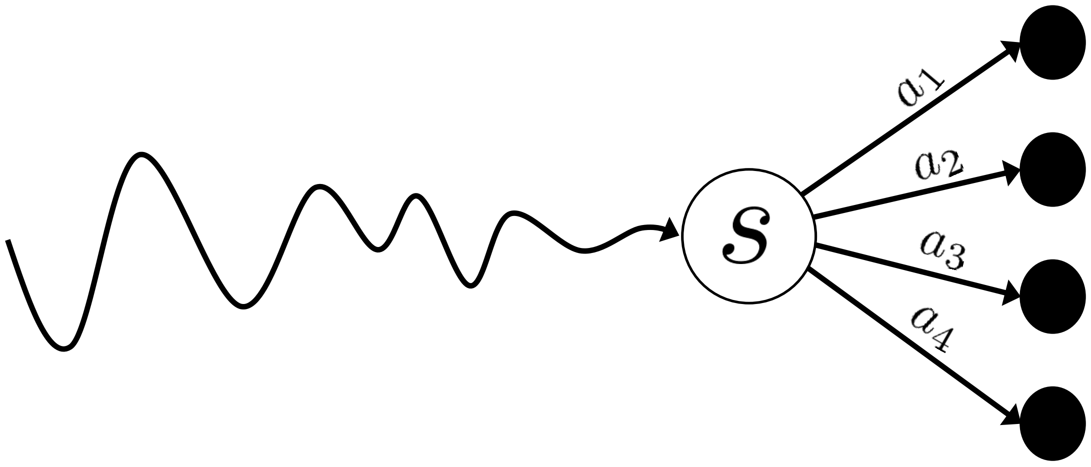

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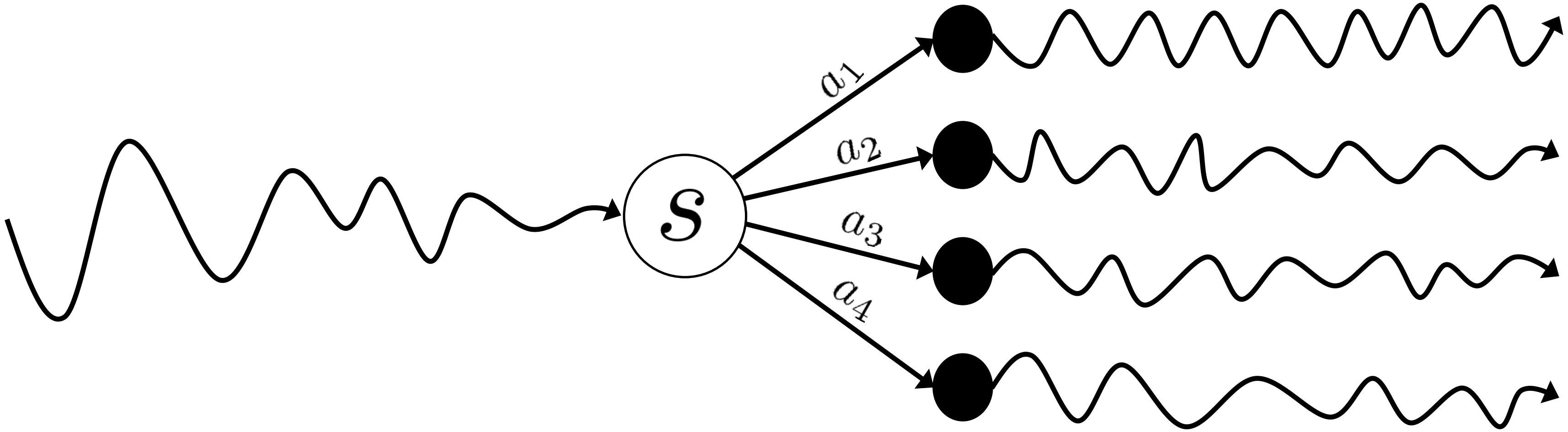

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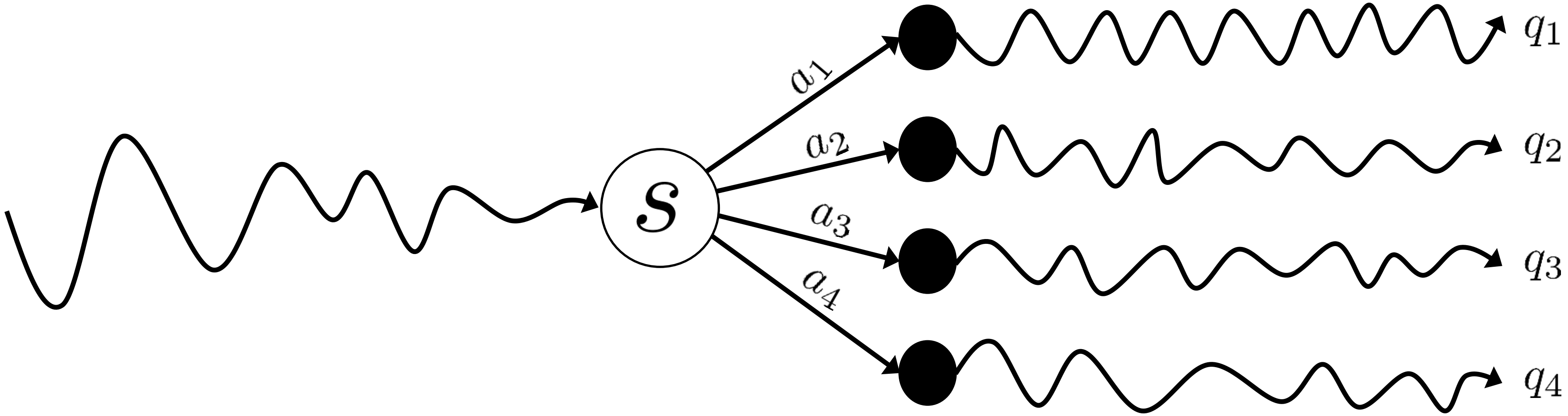
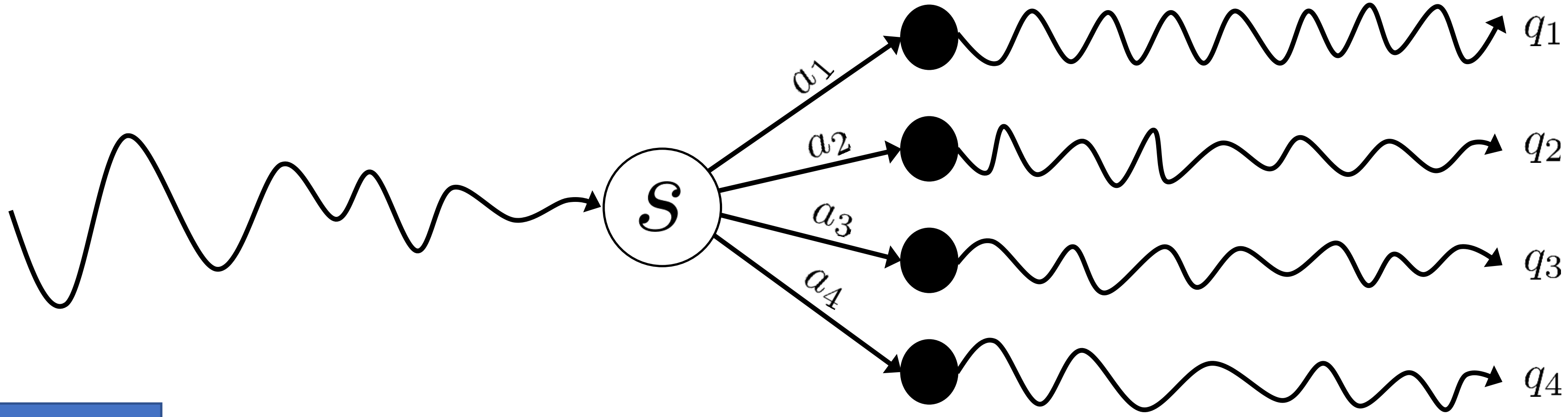


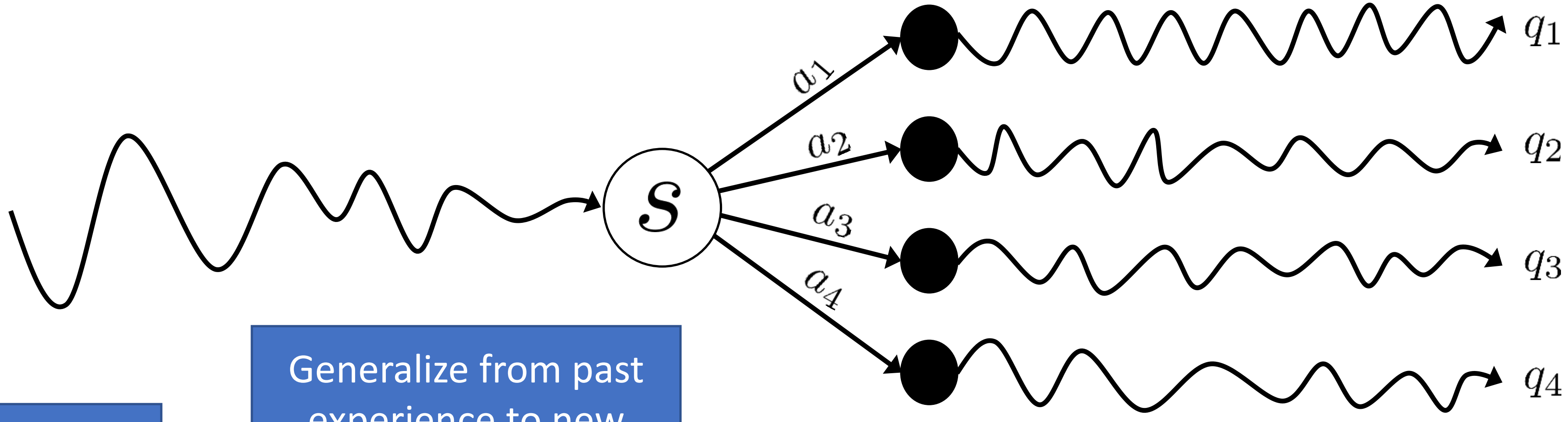
Life of π



Use ML to predict future costs!

$$\mathbb{E}\left[q_i\right] \approx \widehat{q}(s, a_i)$$

Life of π



Use ML to predict future costs!

Generalize from past experience to new situations

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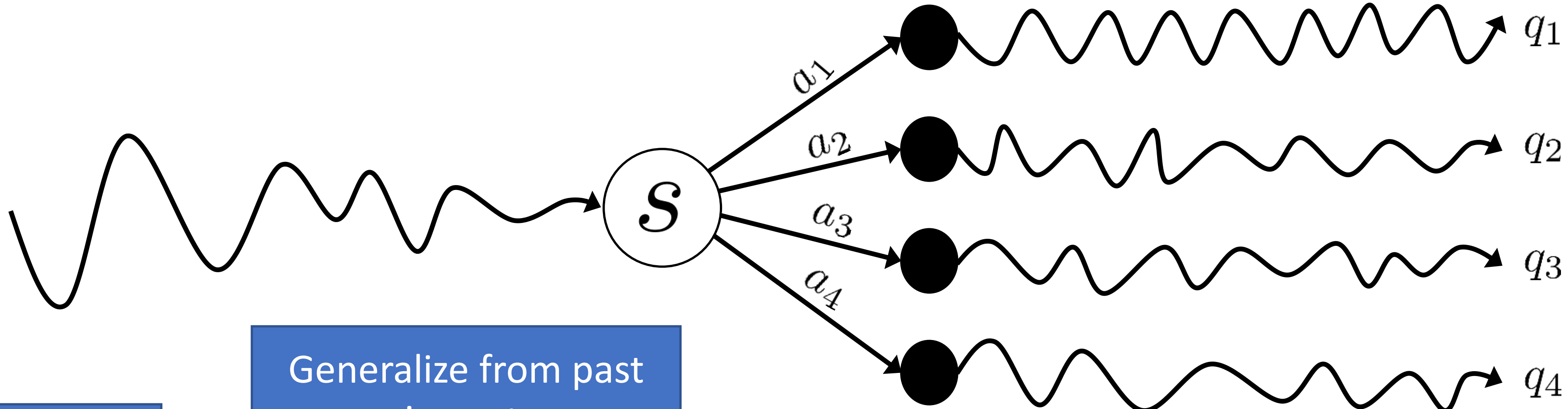
Life of π

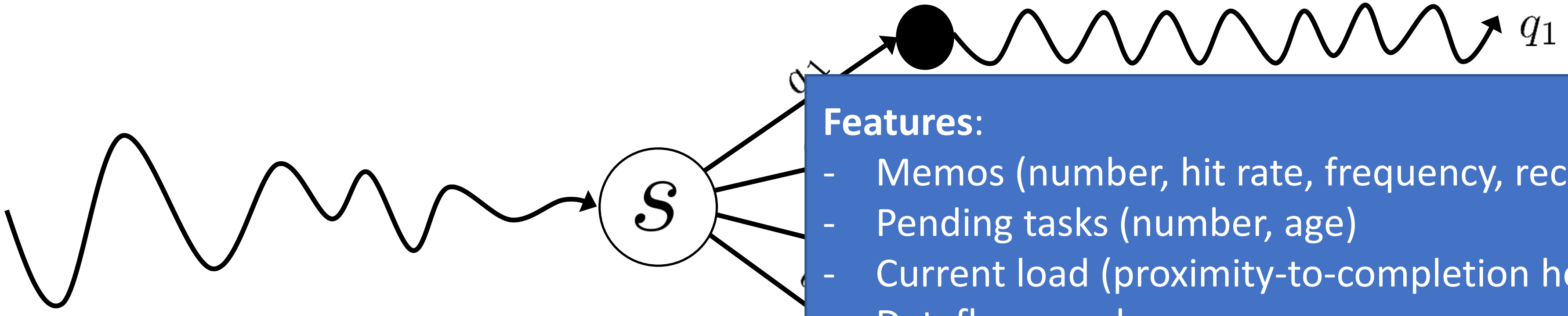


Use ML to predict future costs!

Generalize from past experience to new situations

$$\mathbb{E}\left[q_i\right] \approx \widehat{q}(s, a_i) = w^\top \Phi(s, a_i)$$

Life of π



Features:
- Memos (number, hit rate, frequency, recency)
- Pending tasks (number, age)
- Current load (proximity-to-completion heuristics)
- Dataflow graph
  - Will this be used again?
  - Are other jobs blocking on it?

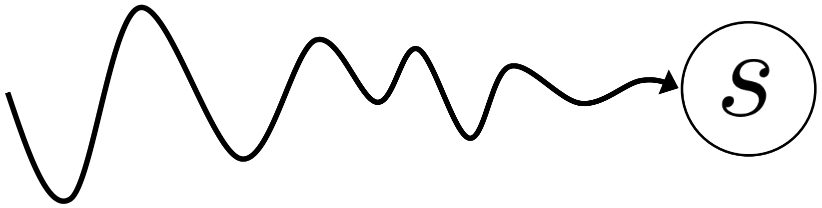
Use ML to predict future costs!

Generalize from past experience to new situations

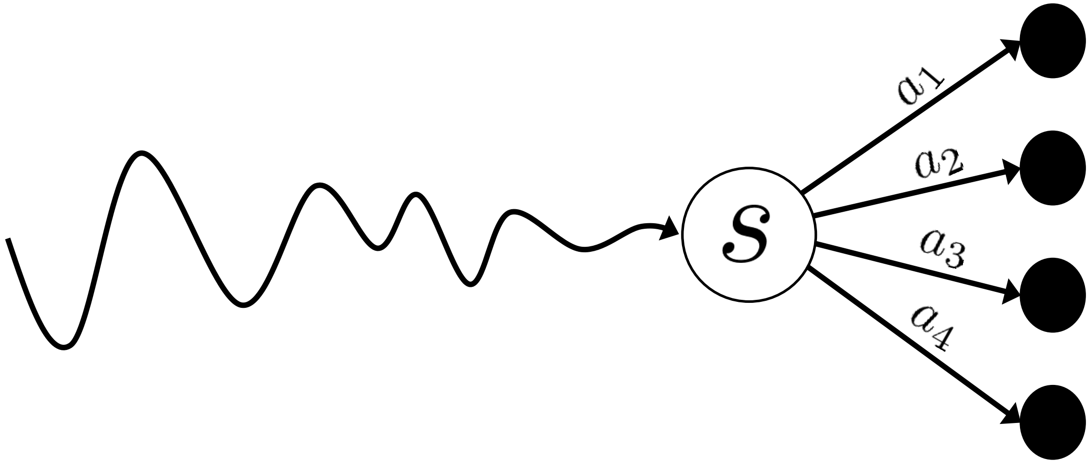
$$\mathbb{E}\left[q_i\right] \approx \widehat{q}(s, a_i) = w^\top \Phi(s, a_i)$$

Back to π

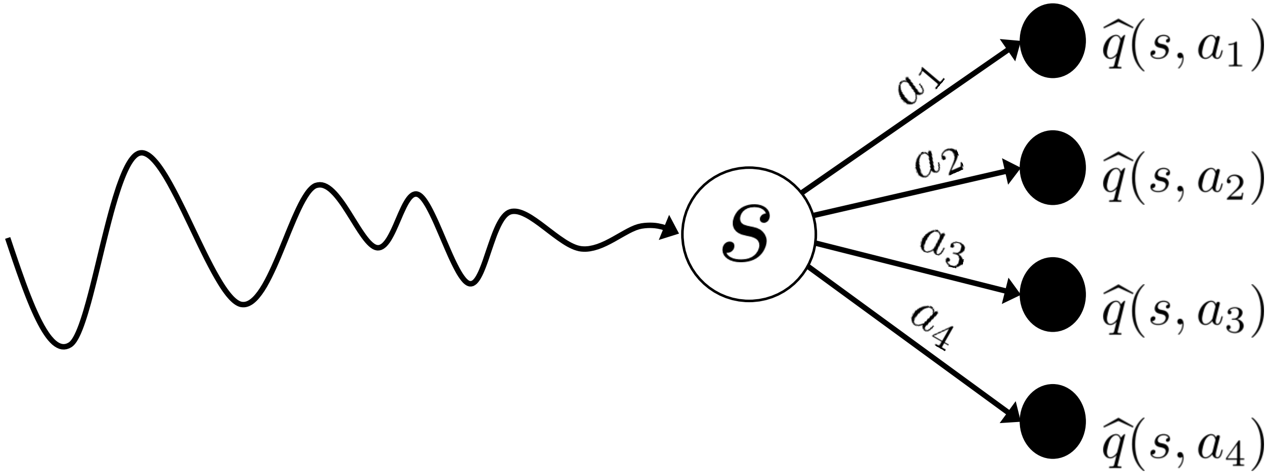
Back to π



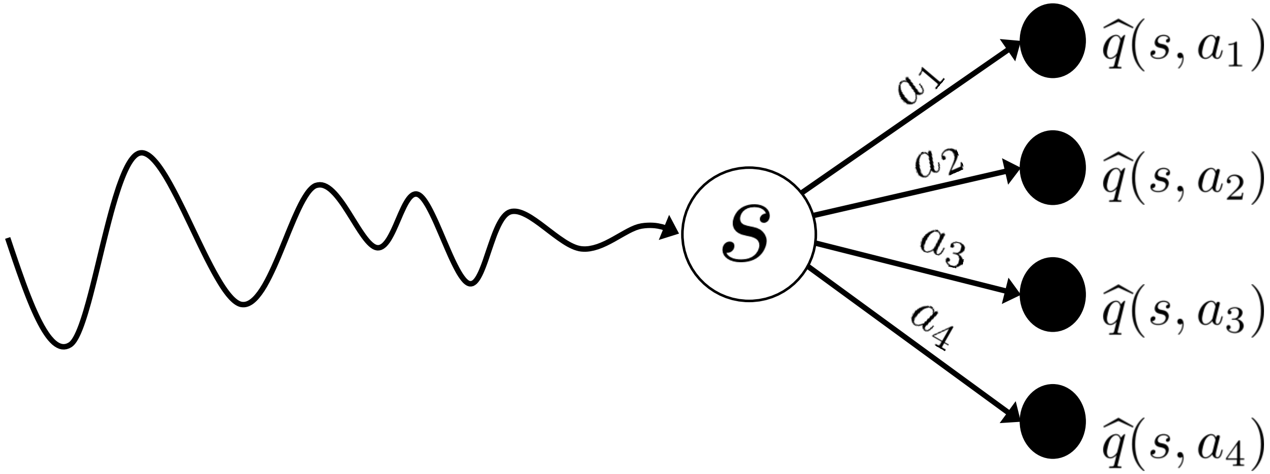
Back to π



Back to π

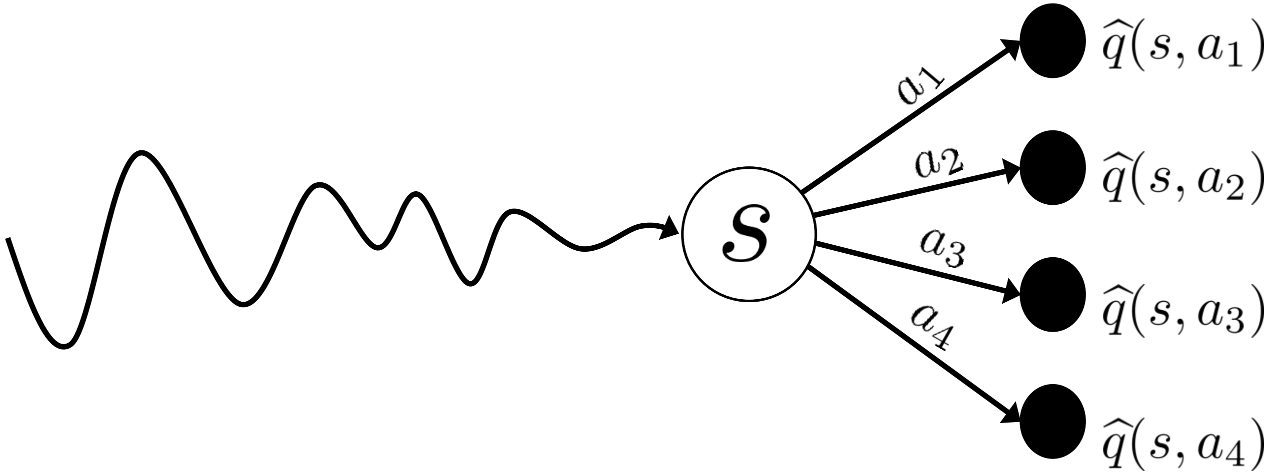

s
a_1
a_2
a_3
a_4
$\widehat{q}(s, a_1)$
$\widehat{q}(s, a_2)$
$\widehat{q}(s, a_3)$
$\widehat{q}(s, a_4)$

Back to π



What should π do in this state?

Back to π



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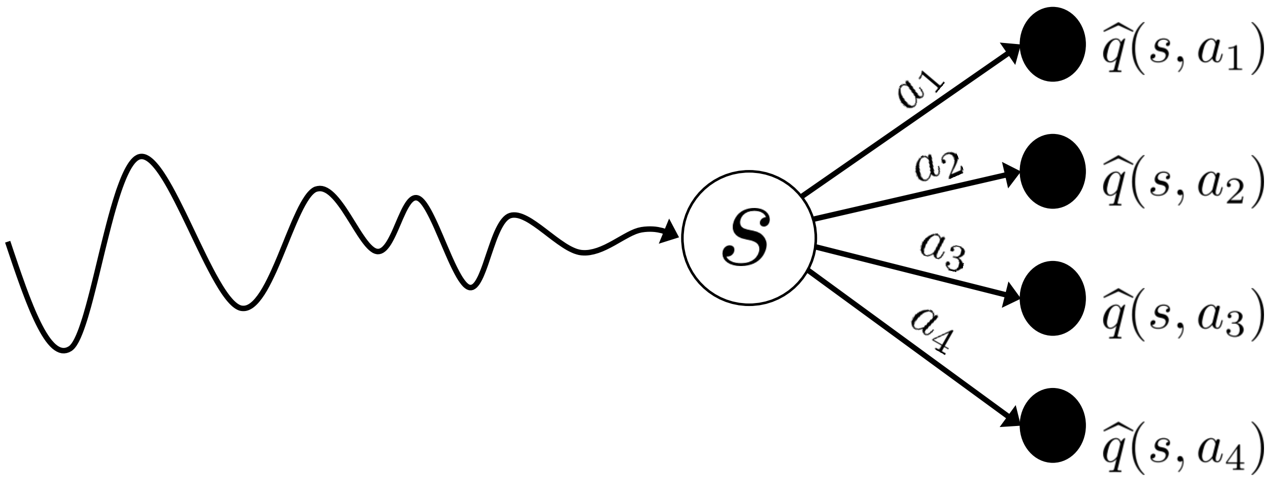
$$\pi(s) = \underset{a}{\operatorname{argmin}} \ \widehat{q}(s, a)$$

Back to π



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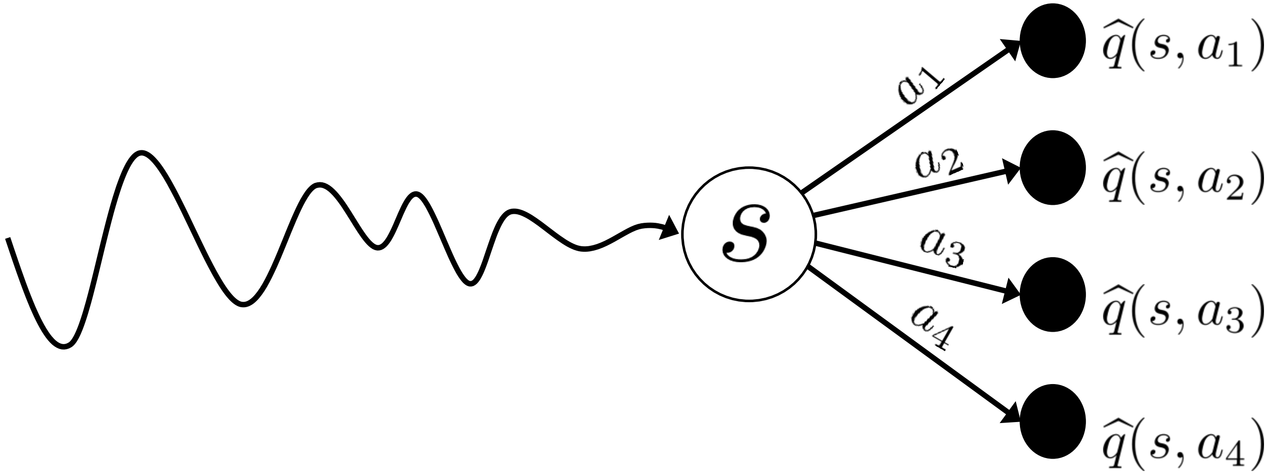
Predicting the future requires richer features than simply learning to take good actions.

Back to π



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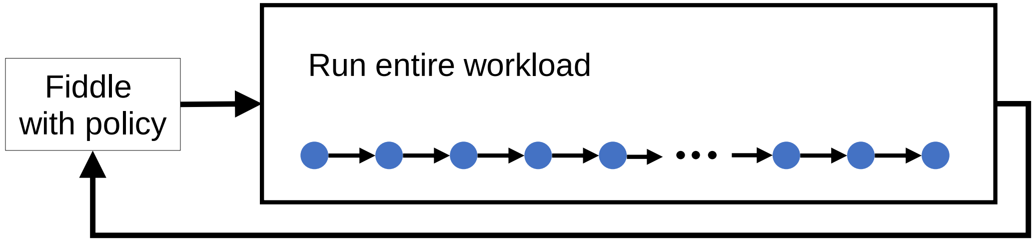
Predicting the future requires richer features than simply learning to take good actions.

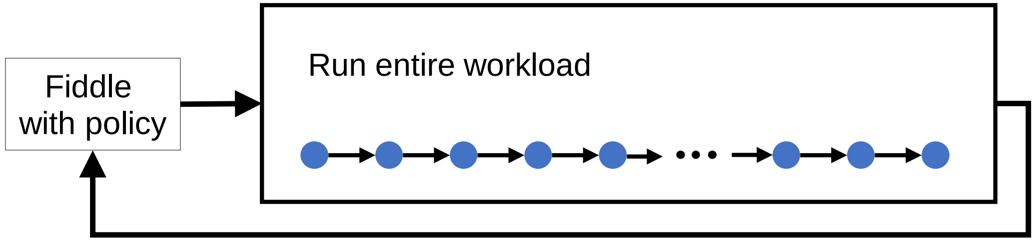
We need π to be really fast to execute!



Fiddle with policy

Run entire workload

Feedback $\rho(\pi)$



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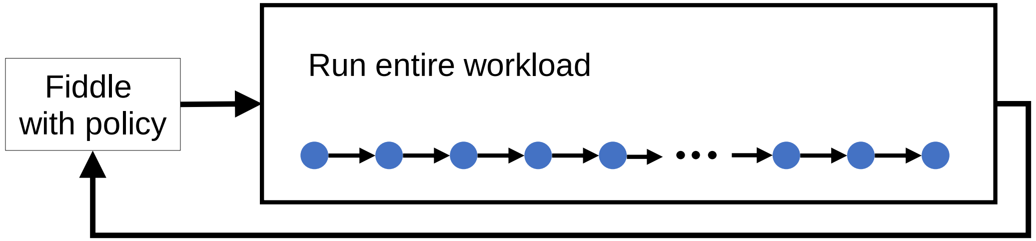

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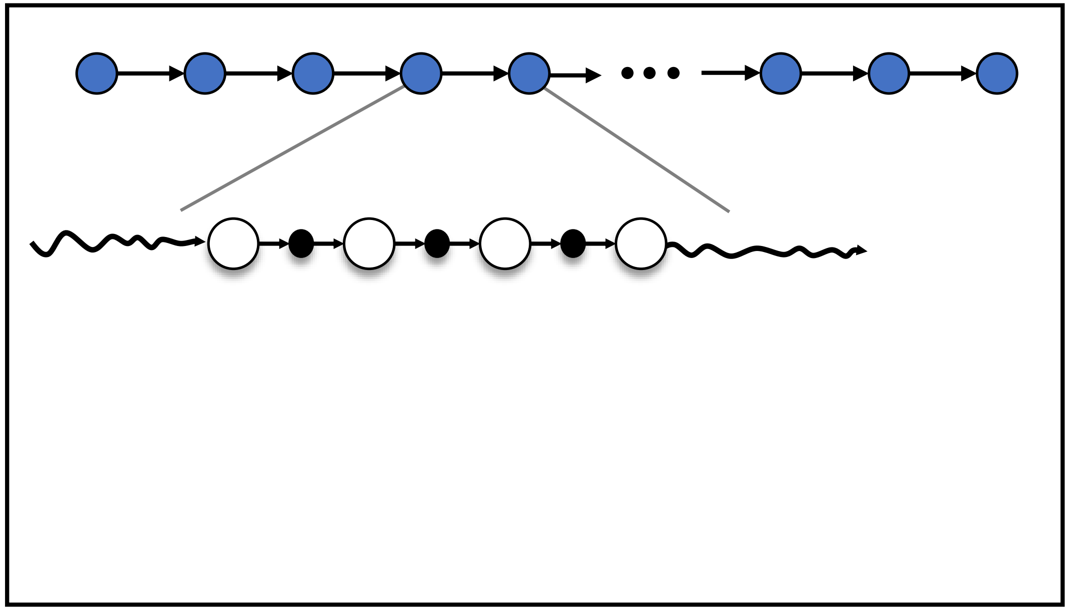

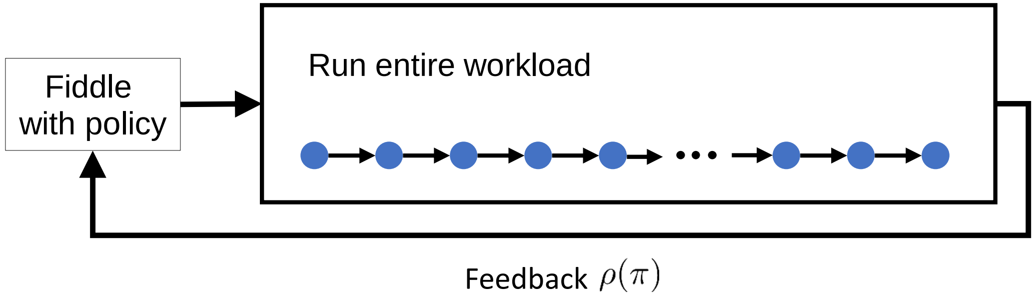

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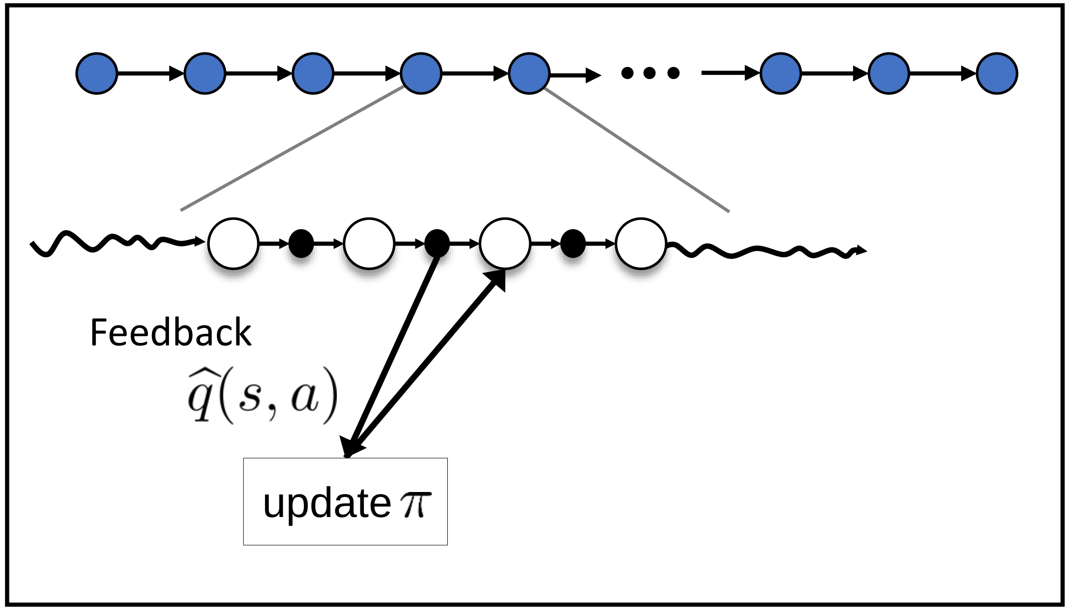
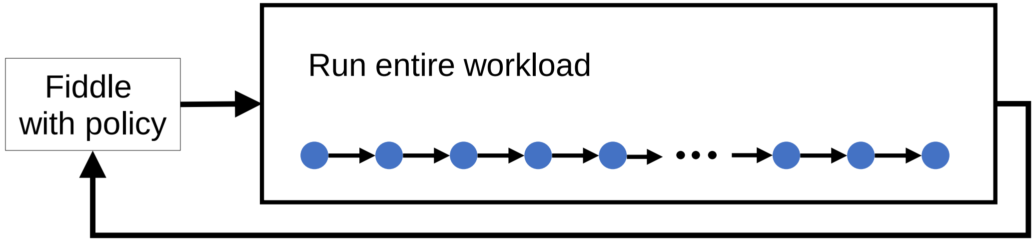


Feedback $\widehat{q}(s,a)$

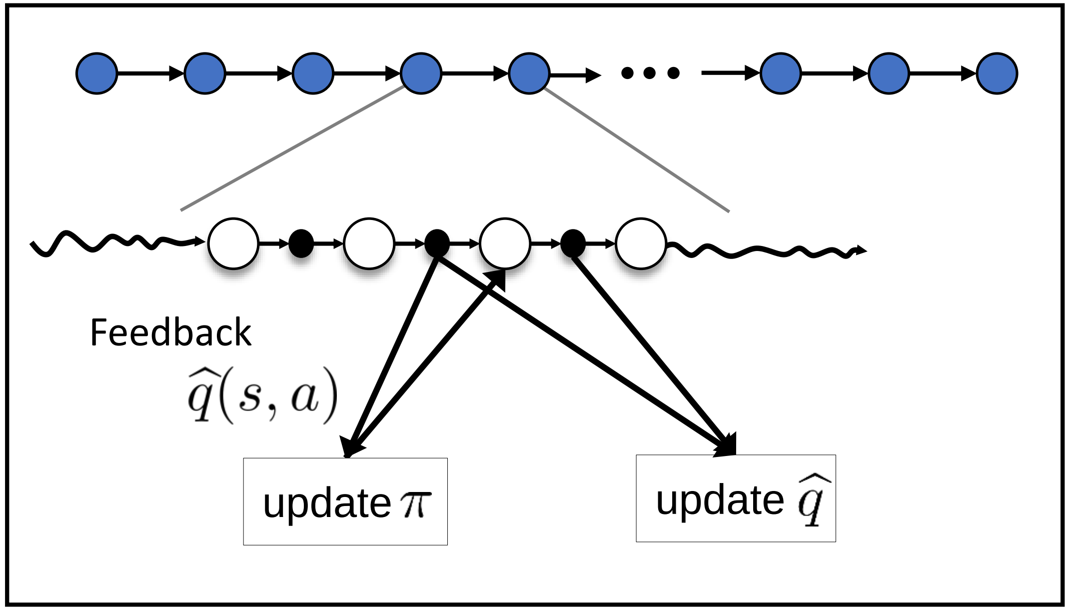
update π



Fiddle with policy

Run entire workload

Feedback $\rho(\pi)$



Feedback $\widehat{q}(s, a)$

update π

update $\widehat{q}$