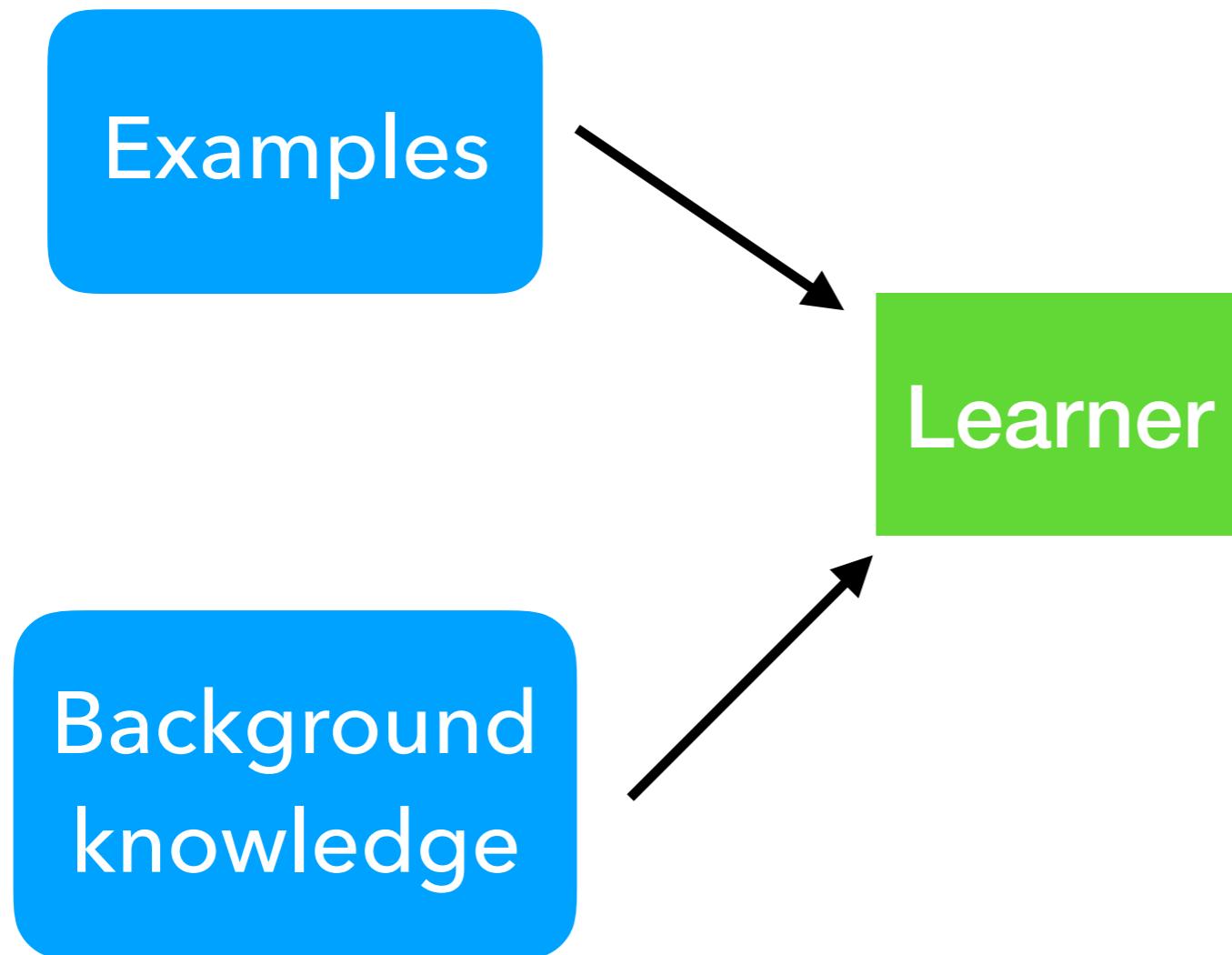


Forgetting to learn logic programs

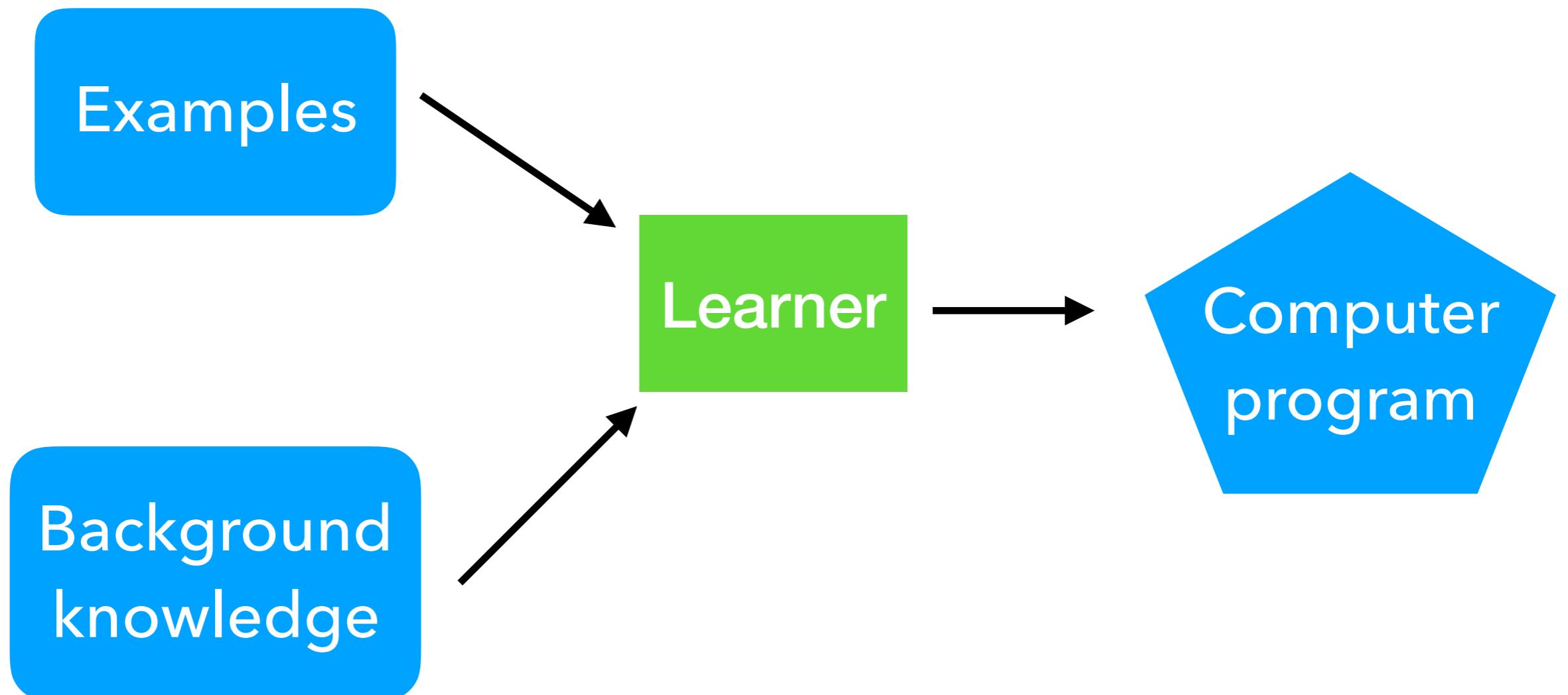
Andrew Cropper

University of Oxford

Program induction/synthesis



Program induction/synthesis



Examples

input	output
dog	g
sheep	p
chicken	?

Examples

input	output
dog	g
sheep	p
chicken	?

Background knowledge

head

tail

empty

Examples

input	output
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sheep	p
chicken	?

Background knowledge

head

tail

empty

```
def f(a):
    t = tail(a)
    if empty(t):
        return head(a)
    return f(t)
```

Examples

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chicken	n

Background knowledge

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tail

empty

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def f(a):
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    return f(t)
```

Examples

input	output
dog	g
sheep	p
chicken	n

Background knowledge

head
tail
empty

```
f(A,B):-tail(A,C),empty(C),head(A,B).  
f(A,B):-tail(A,C),f(C,B).
```

**Background knowledge defines
the hypothesis space**

Where does background knowledge come from?

Hand-crafted rules

[almost every approach]

Unsupervised learning

ALPS [Dumančić et al. IJCAI 2019]

Playgol [Cropper. IJCAI 2019]

Supervised multi-task learning

Use knowledge gained from solving one problem to help solve a different problem

Metabias [Lin et al. ECAI 2014]

Dreamcoder [Ellis et al. NIPS 2018]

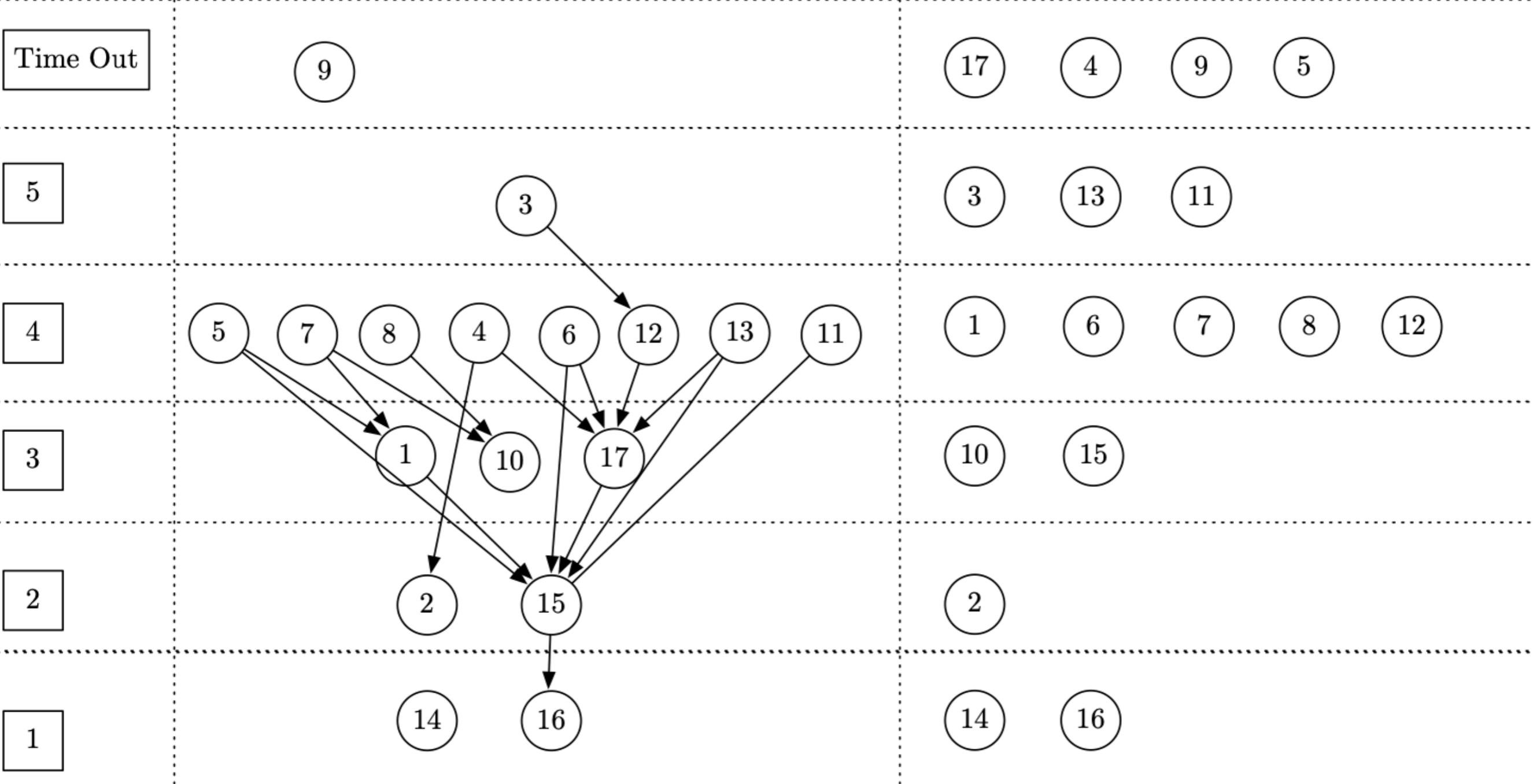
Why does it work?

We increase branching but reduce depth

Size Bound

Dependent Learning

Independent Learning

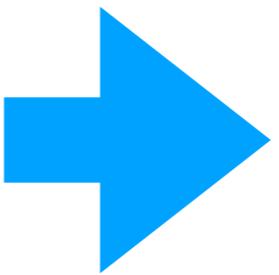


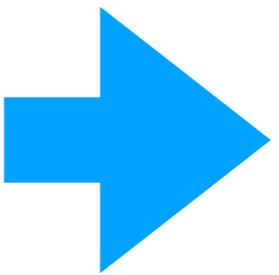
Problem: big branching factor



Idea

Forget things





ILP problem

Given:

- background knowledge **B**
- positive examples **E+**
- negative examples **E-**

ILP problem

Return:

A hypothesis **H** that with **B** entails **E+** and not **E+**

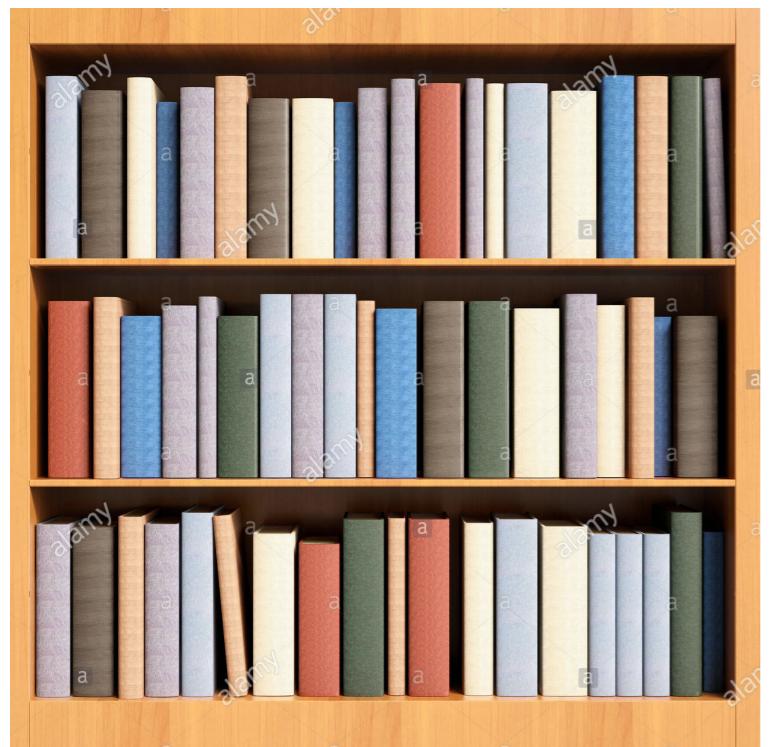
Forgetting problem

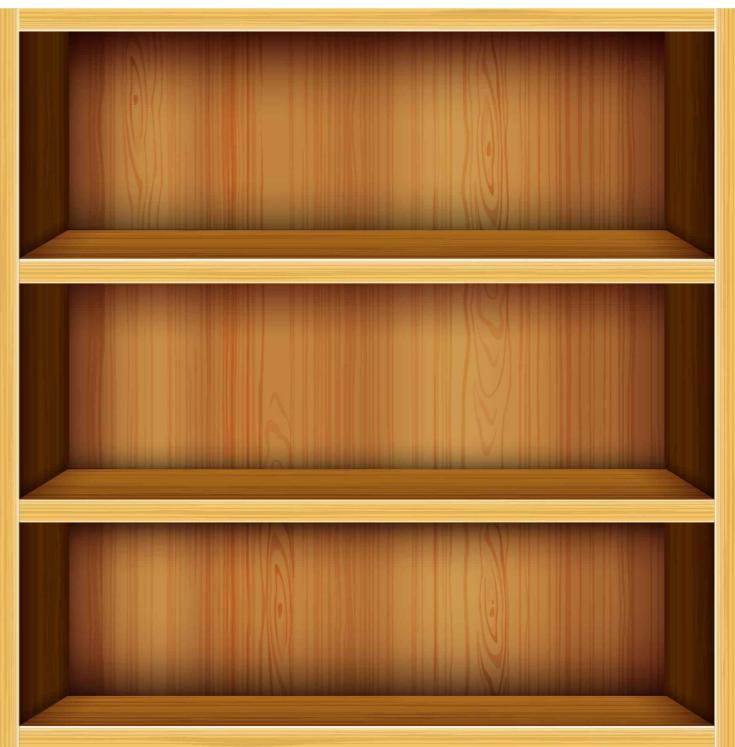
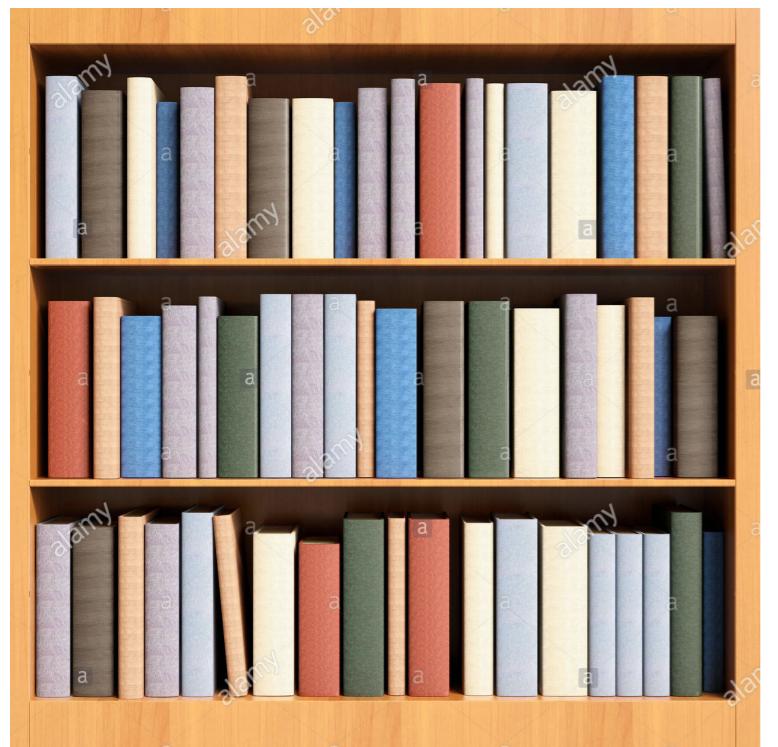
Given background knowledge \mathbf{B}

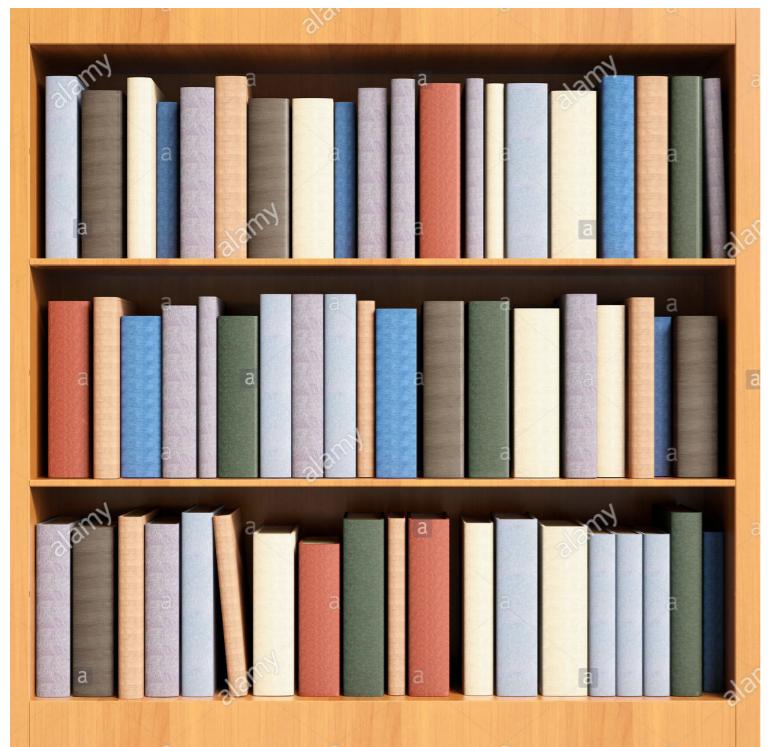
Return $\mathbf{B}' \subset \mathbf{B}$ from which you can still learn the target hypothesis

Why?

Reduce branching and sample complexity







How?

Forgetgol, a multi-task ILP system based on Metagol, which takes a forgetting function as input

Forgetgol

Continually **expands** and **shrinks** its hypothesis space

Syntactical forgetting (lossless)

1. Unfold each induced clause to remove invented predicate symbols
2. Check whether a syntactically duplicate clause already exists

Statistical forgetting

Assigns a cost to each clause based on:

1. How difficult it was to learn
2. How likely it is to be reused

Does it work?

Q. Can forgetting improve learning performance?

We compare:

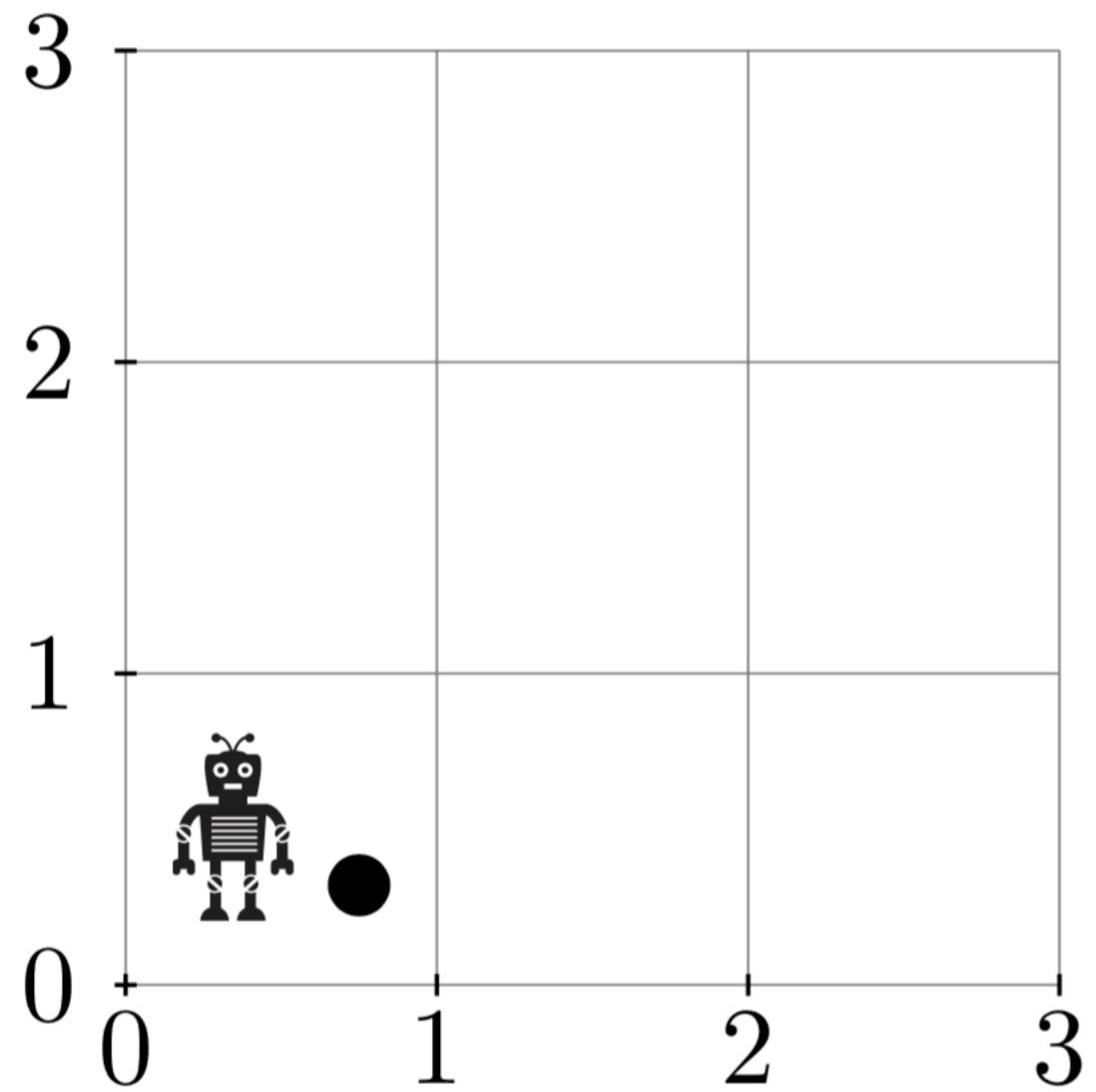
Metabias: remember everything

Metagol: remember nothing

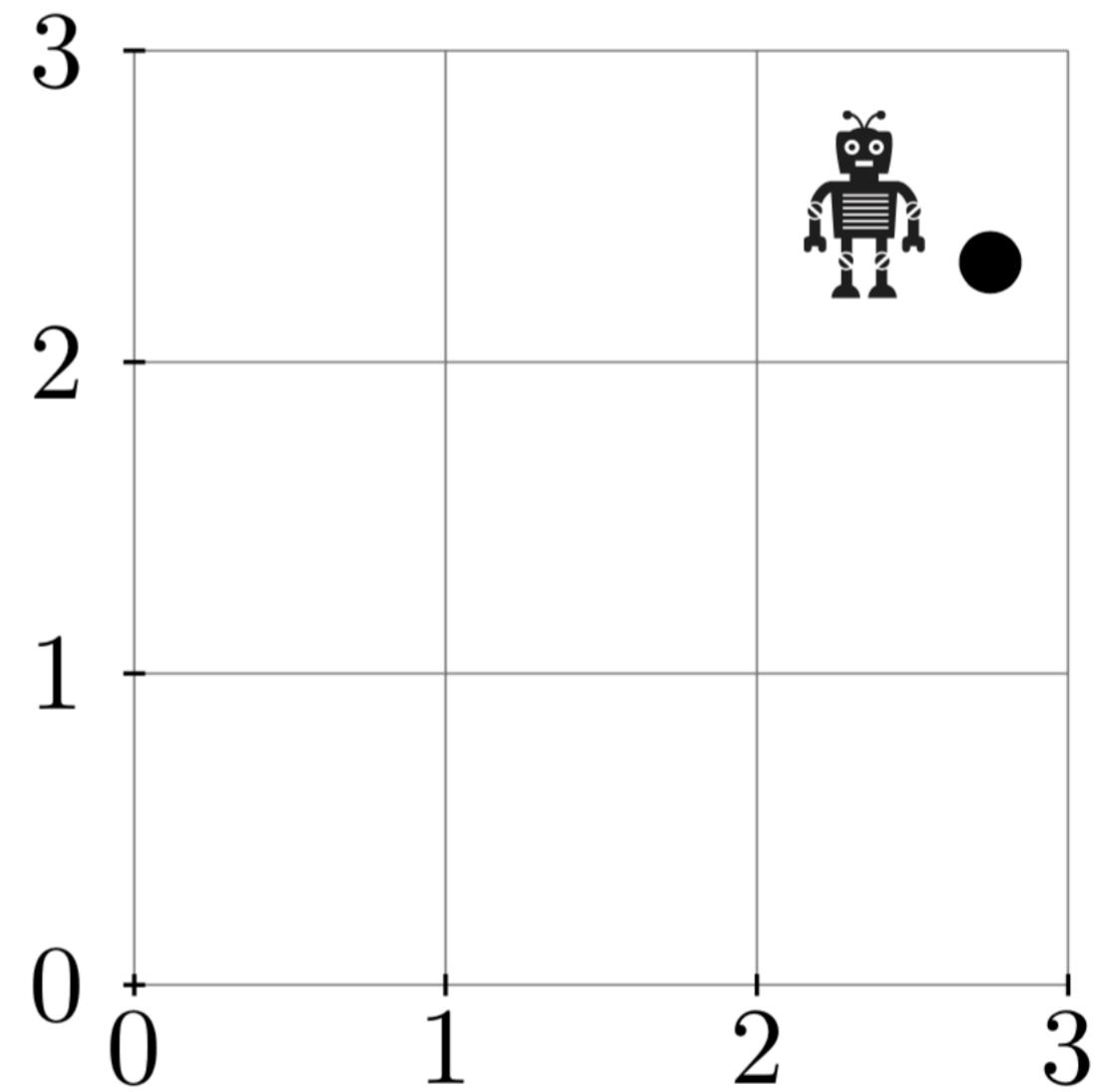
Forgetgol_{syn}: syntactical forgetting

Forgetgol_{stat}: statistical forgetting

Robot planning



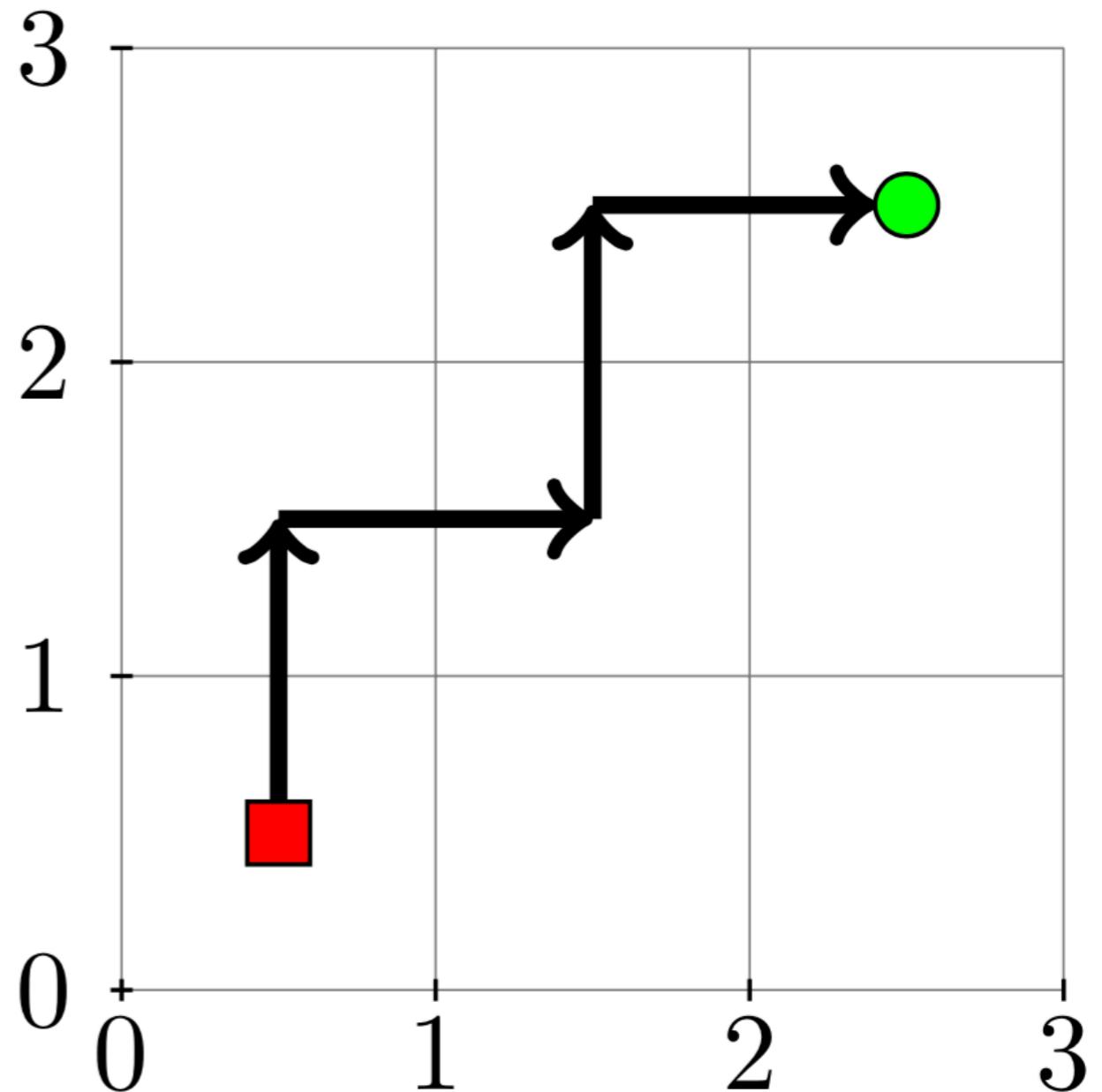
(a) Initial state



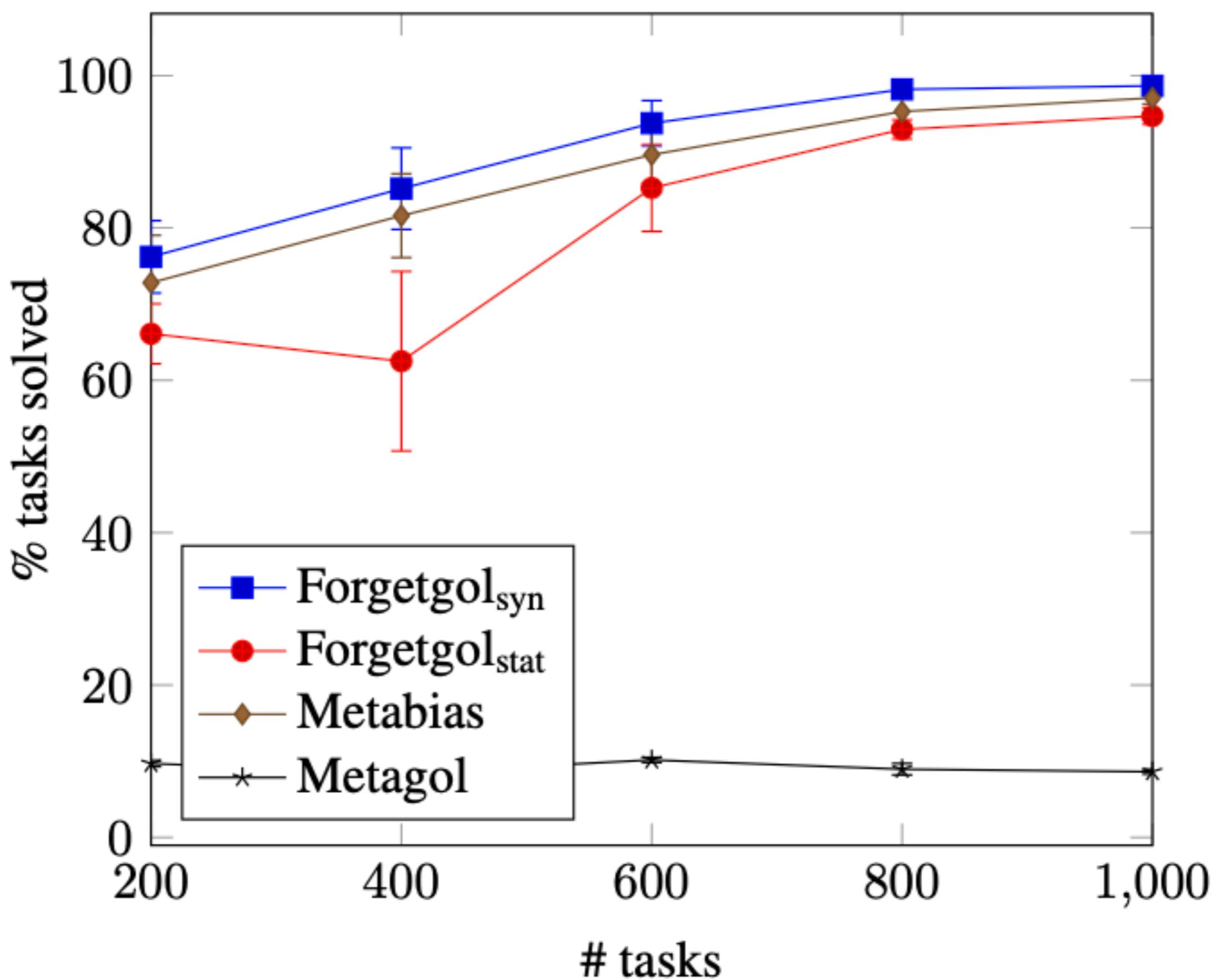
(b) Final state

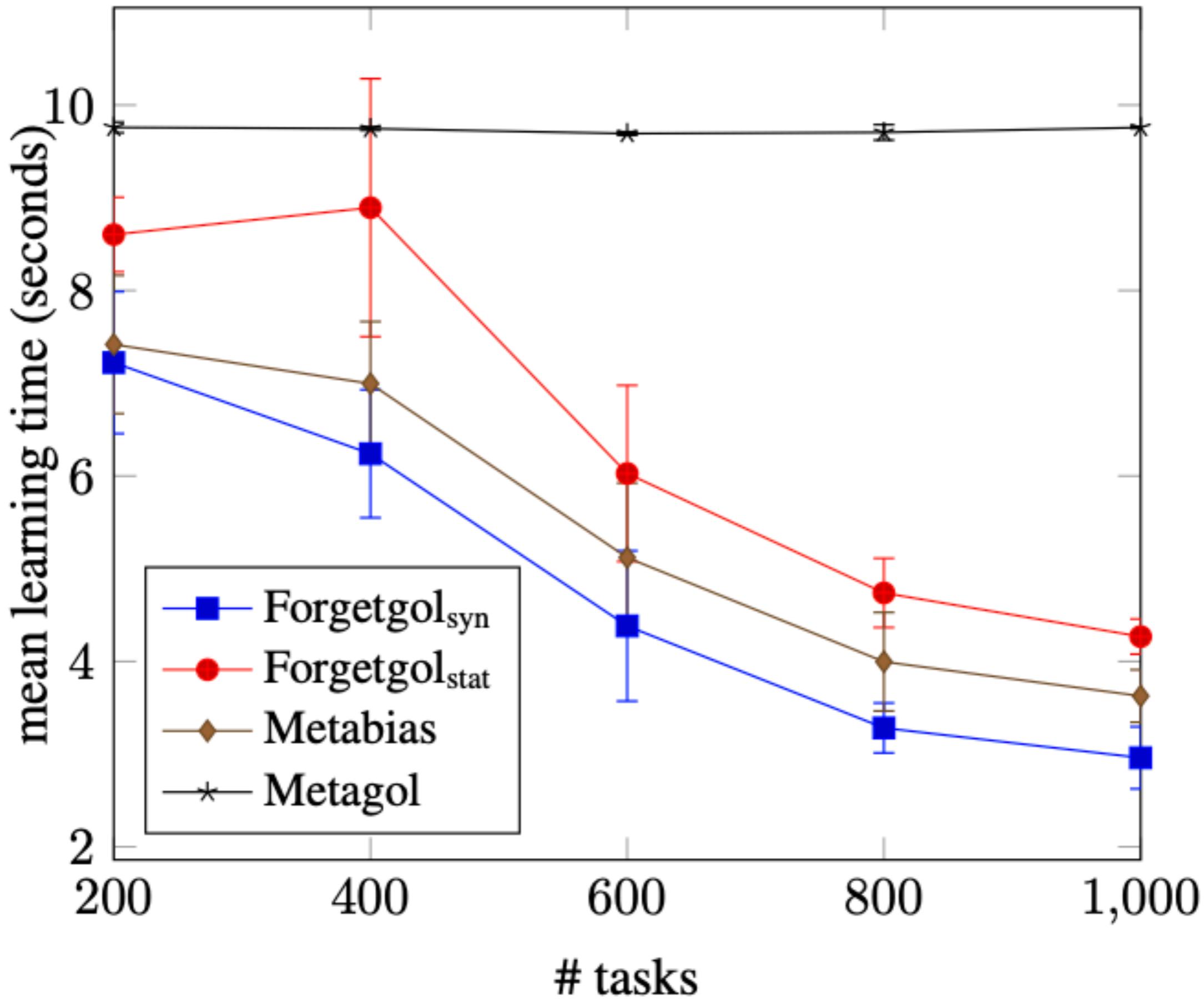
```
f(A,B) :-  
    grab(A,C),  
    f1(C,D),  
    f1(D,E),  
    drop(E,B).  
  
f1(A,B) :-  
    up(A,C),  
    right(C,B).
```

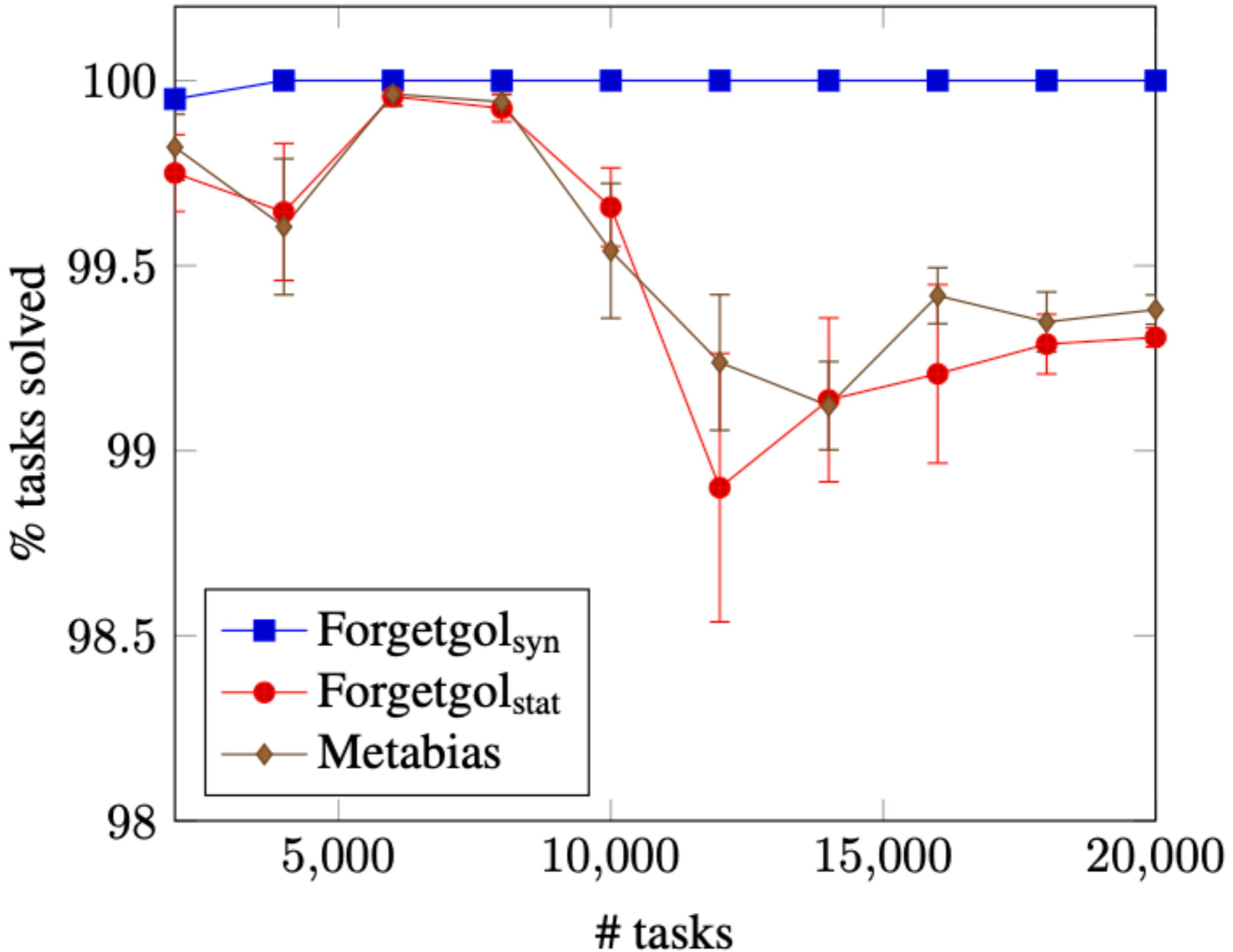
(a) Program

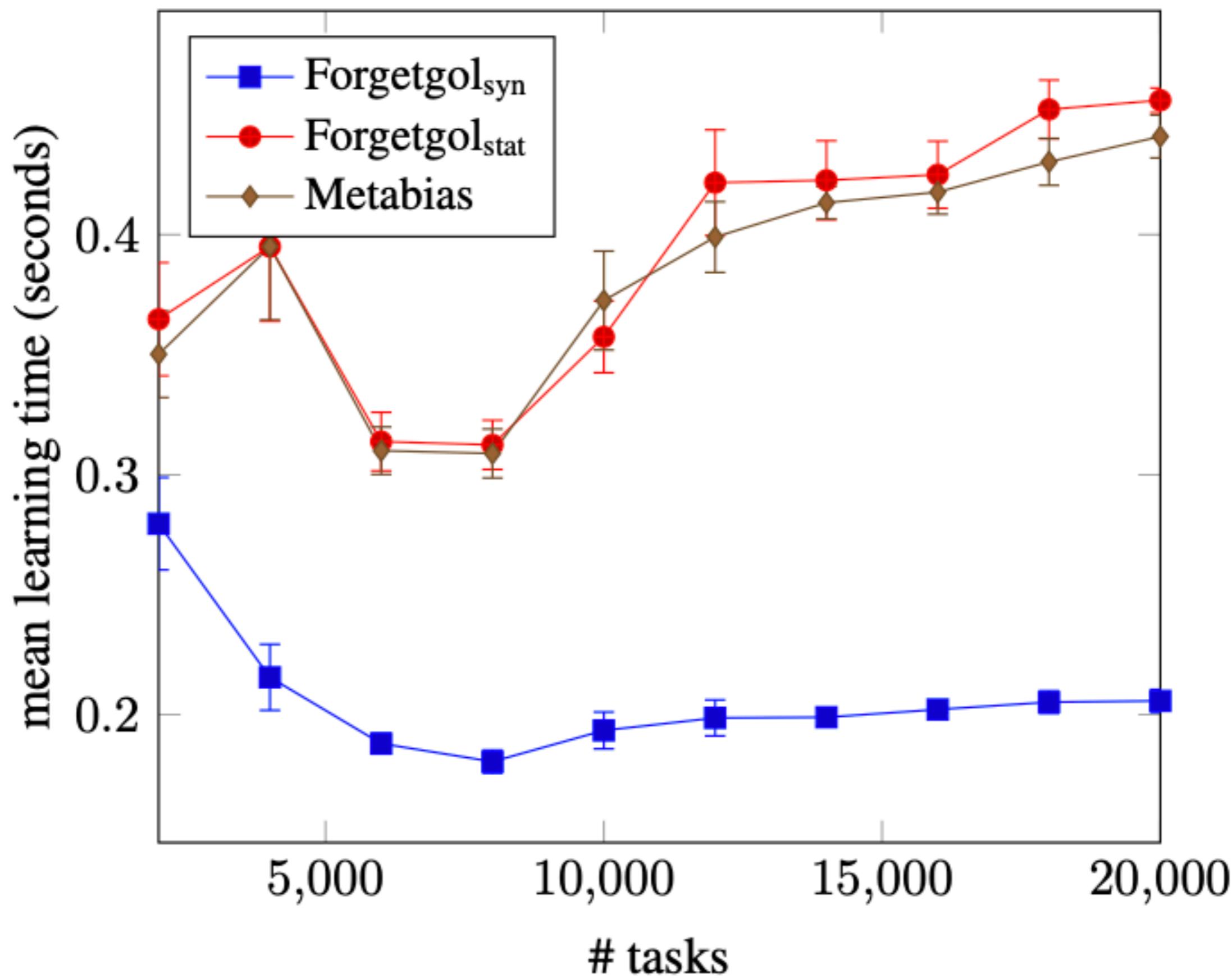


(b) Plan







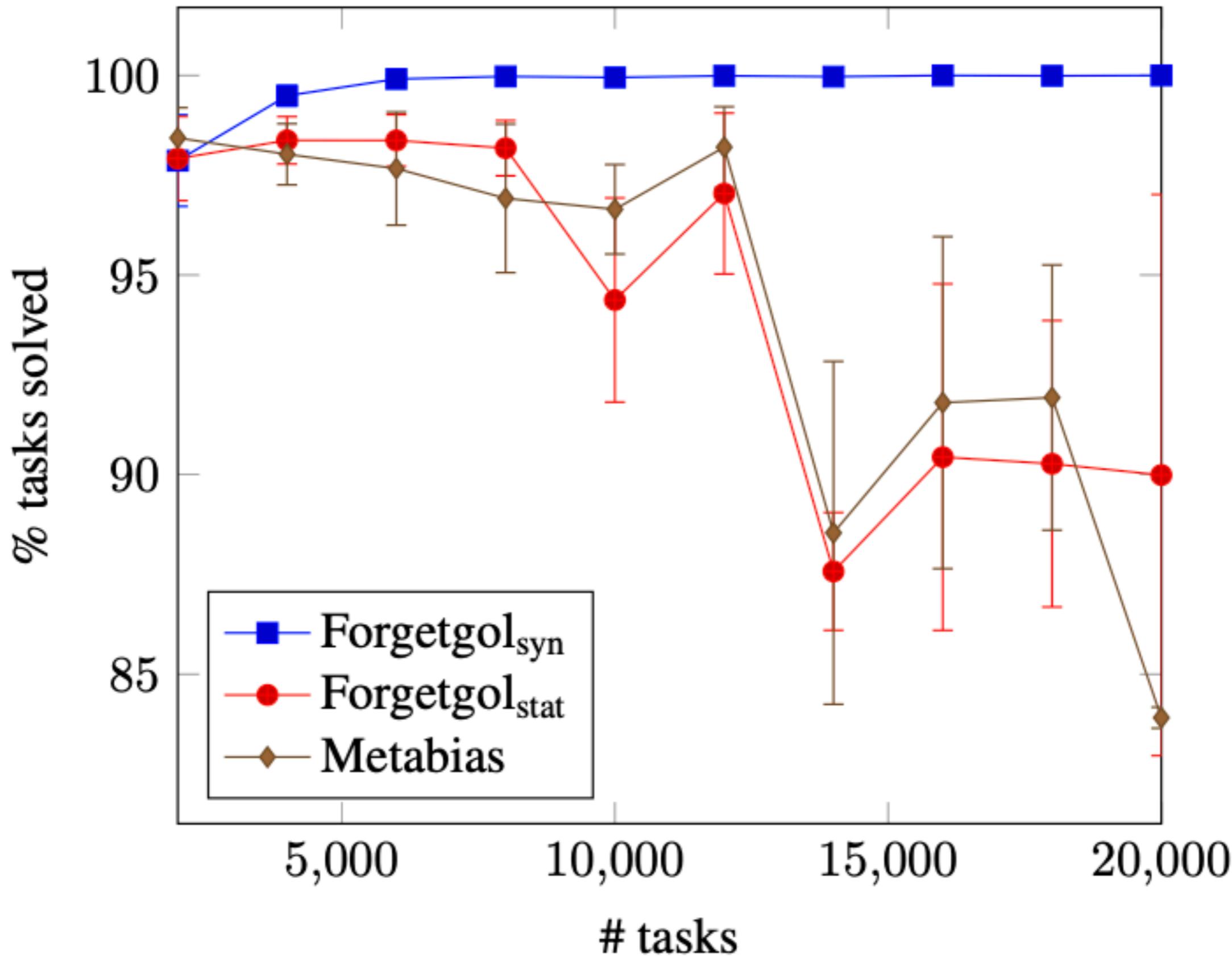


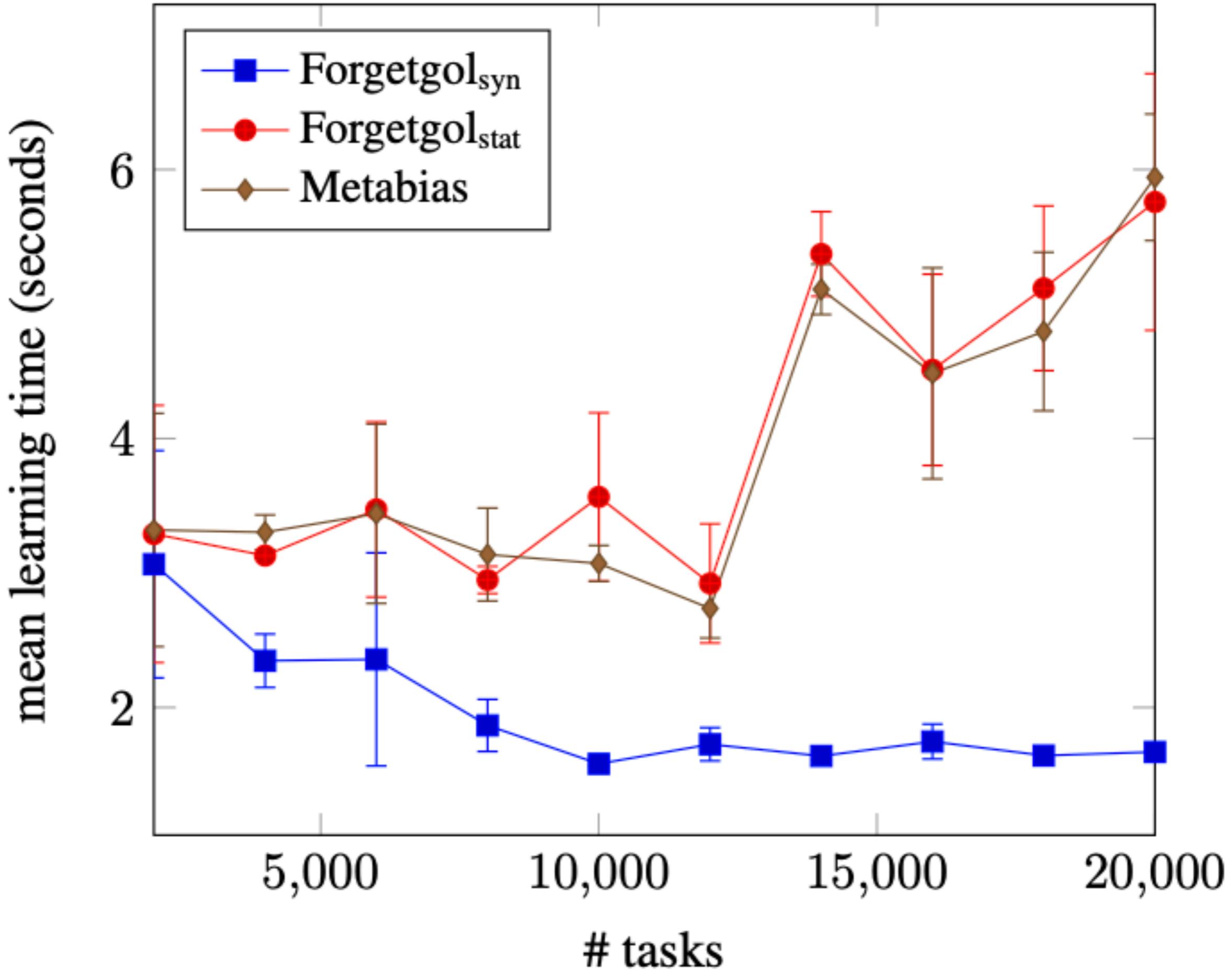
What happened?

Metabias rarely induces a program with more than two clauses because of program reuse



Lego building





What happened?

Less reuse (and greater search depth) so
forgetting has more effect

Conclusions

Forgetting can improve learning performance when given >10,000 tasks, but, surprisingly, not by much

Limitations and future work

Better forgetting methods

Larger and more diverse datasets

Concept shift

Recency

Other program induction systems