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# Learning MDL logic programs from noisy data

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UK Research  
and Innovation



# Inductive Logic Programming

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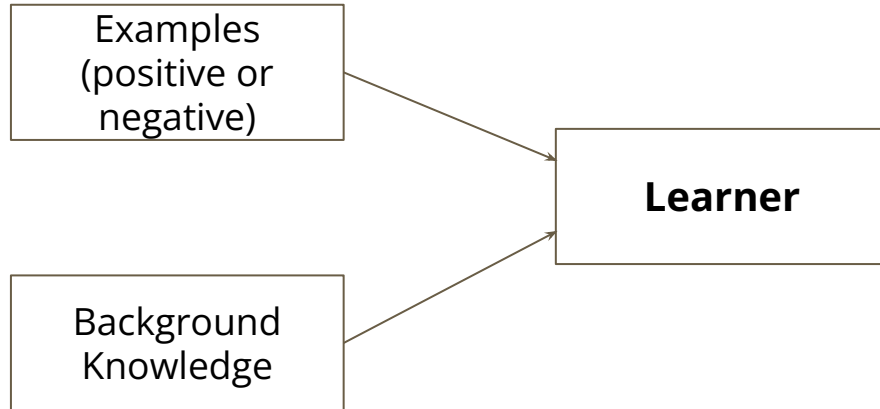
Examples  
(positive or  
negative)

# Inductive Logic Programming

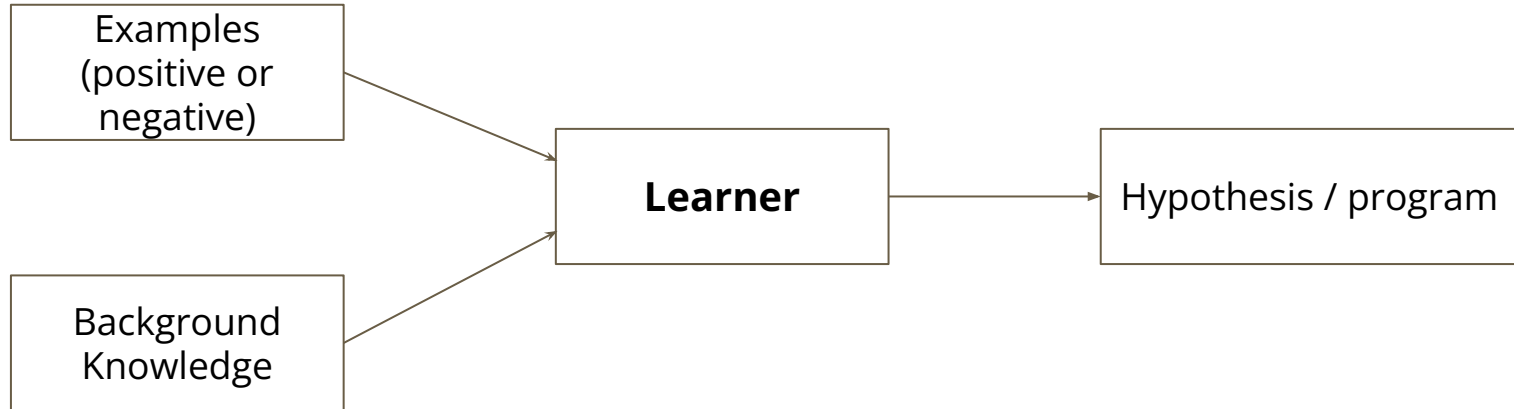
Examples  
(positive or  
negative)

Background  
Knowledge

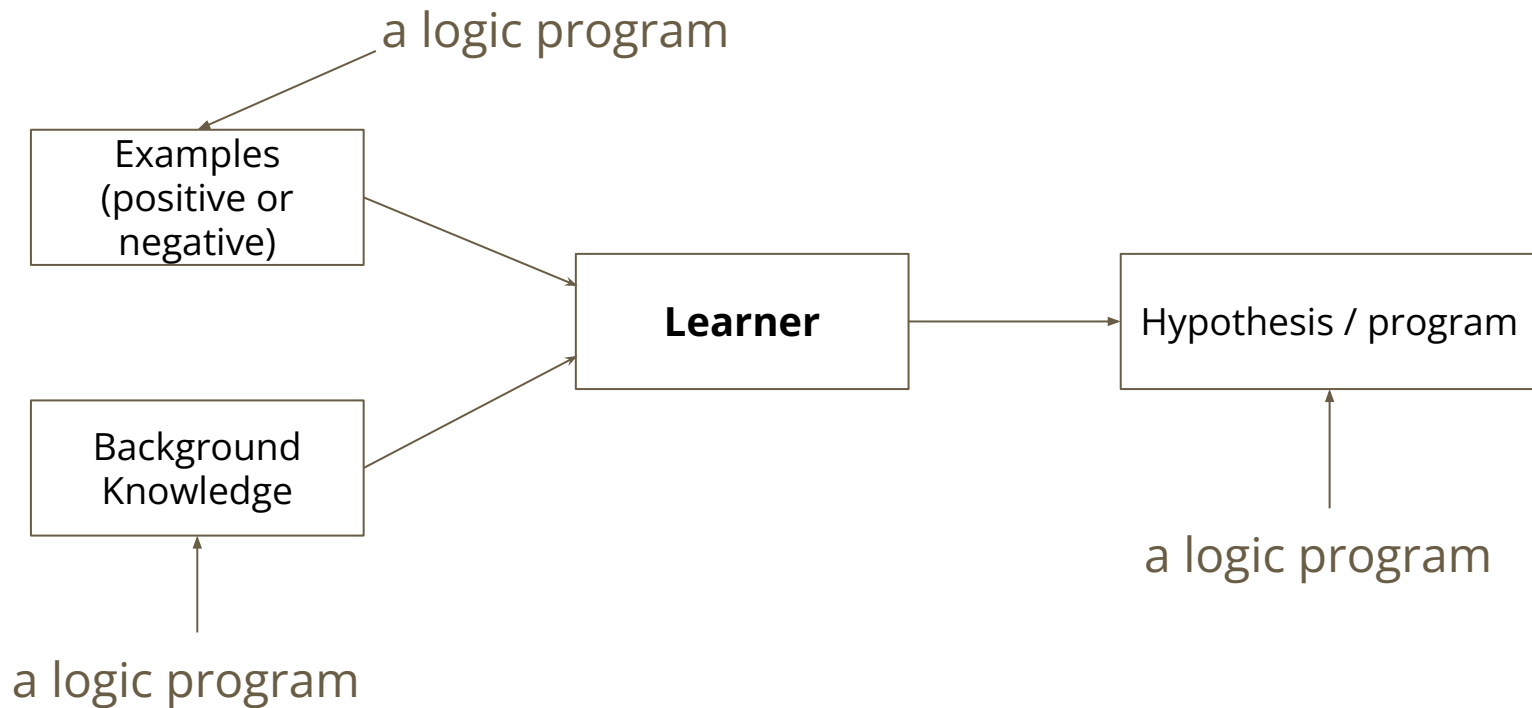
# Inductive Logic Programming



# Inductive Logic Programming



# Inductive Logic Programming



Positive

X	X	X
O	X	O
		O

X	X	O
	O	O
X	X	O

O	X	O
X	O	X
		O



Positive

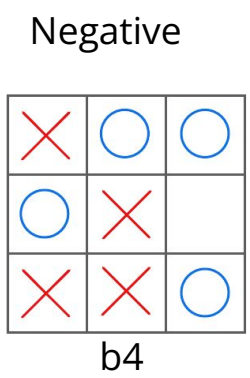
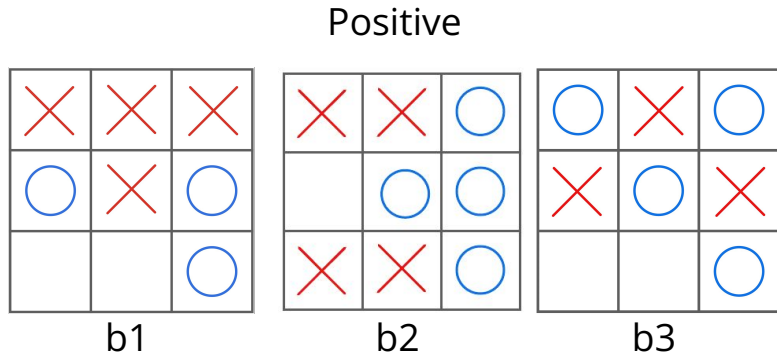
X	X	X
O	X	O
		O

X	X	O
	O	O
X	X	O

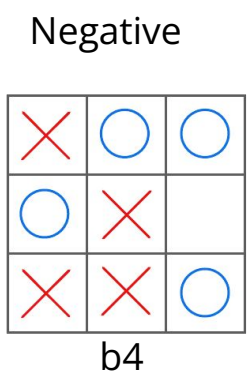
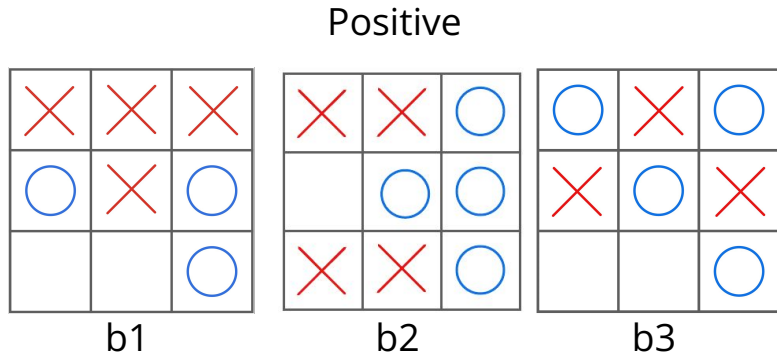
O	X	O
X	O	X
		O

Negative

X	O	O
O	X	
X	X	O



Positive examples	Negative examples
<code>win(b1,x).</code> <code>win(b2,o).</code> <code>win(b3,o).</code>	<code>win(b4,x).</code>



Positive examples	Negative examples
<pre>win(b1,x). win(b2,o). win(b3,o).</pre>	<pre>win(b4,x).</pre>

**Background Knowledge**

```
cell(b1,0,x).
cell(b1,1,x).
cell(b1,2,x).
...
cell(b2,0,x).
...
cell(b3,0,o).
```

0	1	2
3	4	5
6	7	8

Positive

X	X	X
O	X	O
		O

X	X	O
	O	O
X	X	O

O	X	O
X	O	X
		O

Negative

X	O	O
O	X	
X	X	O

Program

```
win(Board,Player) ← cell(Board,0,Player), cell(Board,1,Player), cell(Board,2,Player)
win(Board,Player) ← cell(Board,2,Player), cell(Board,5,Player), cell(Board,8,Player)
win(Board,Player) ← cell(Board,0,Player), cell(Board,4,Player), cell(Board,8,Player)
```

0	1	2
3	4	5
6	7	8

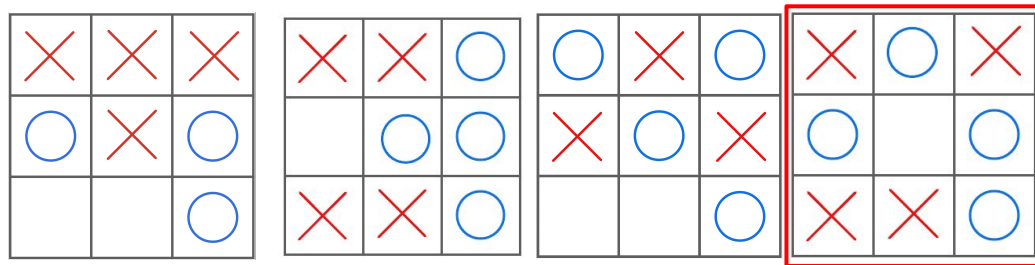
# In this work

An approach to learn programs from noisy (mislabelled) examples

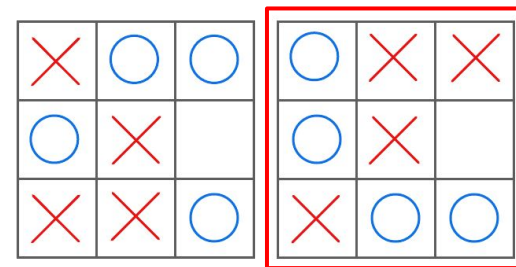
# In this work

An approach to learn programs from noisy (mislabelled) examples

Positive



Negative



# Challenges

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- unspecified level of noise  $\varepsilon$



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- unspecified level of noise  $\epsilon$
- overfitting

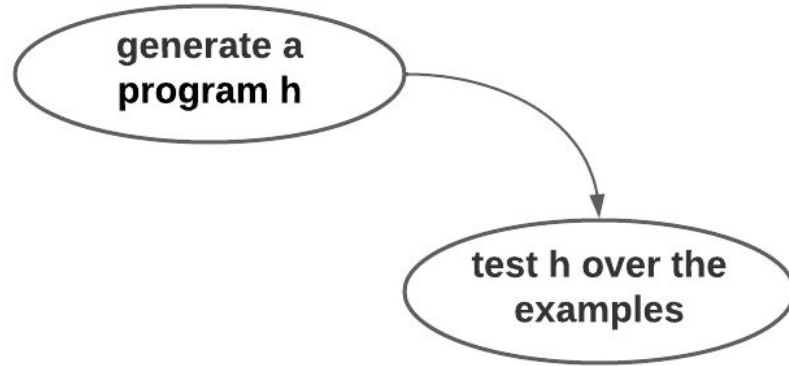
# Challenges

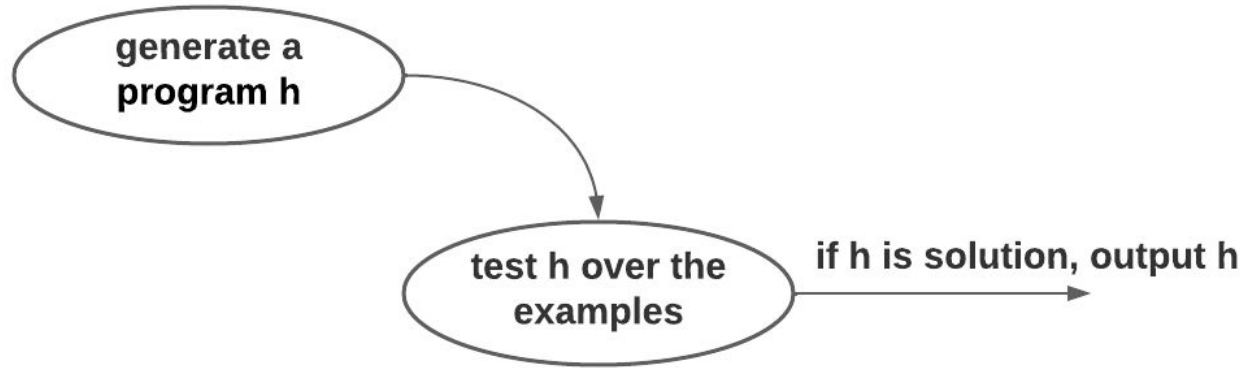
- unspecified level of noise  $\epsilon$
- overfitting
- learn complex programs (recursion and predicate invention)

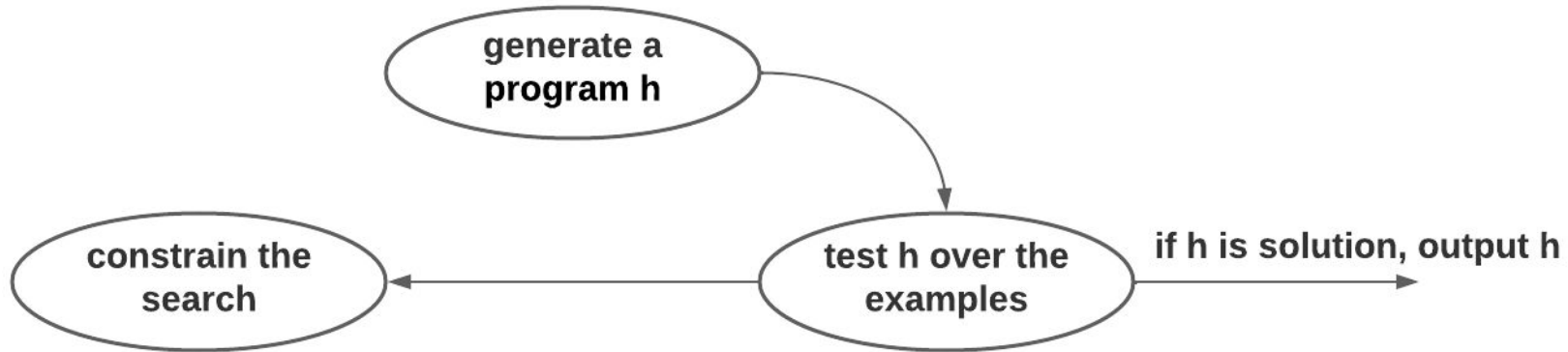
**Our approach: based on learning from failures**

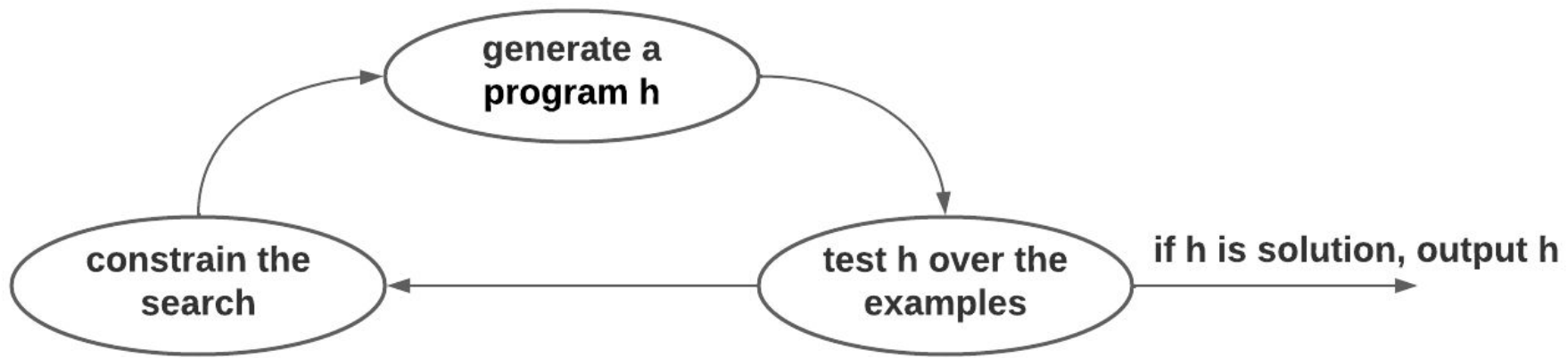


**generate a  
program h**

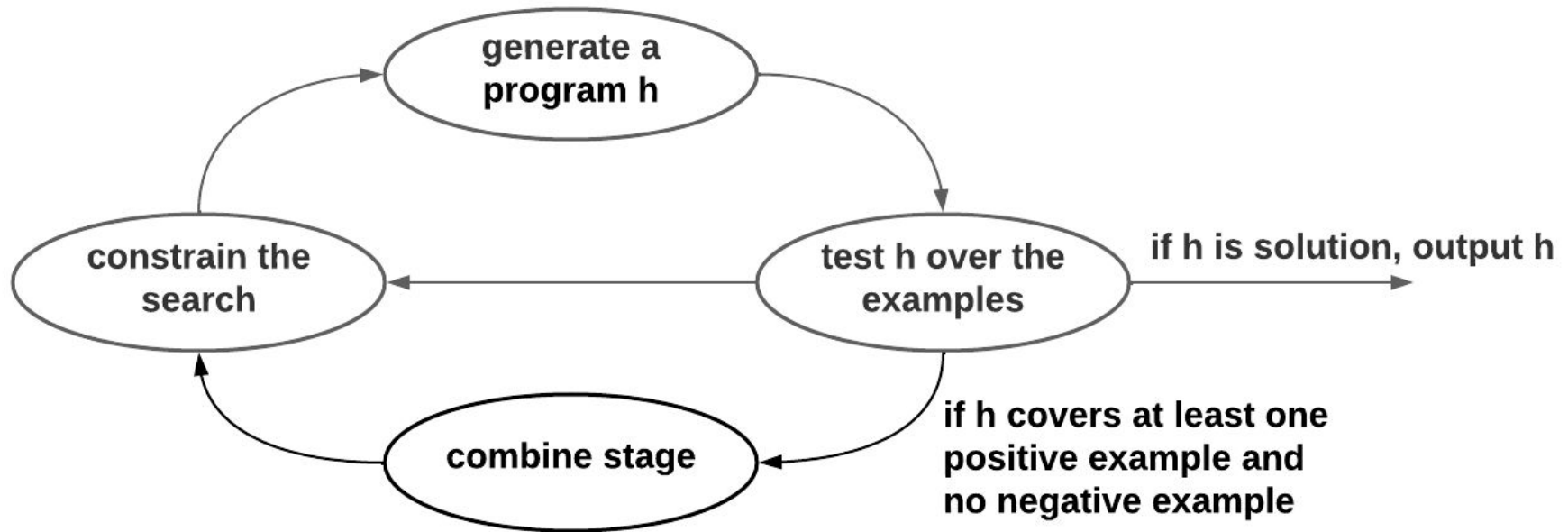












# Existing approaches

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find a program which covers all positive examples, no negative examples and has minimal size

# Our cost function

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minimum description length: trade-off model complexity (program size) and data fit (training accuracy)

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$$mdl(h) = size(h) + fp(h) + fn(h)$$

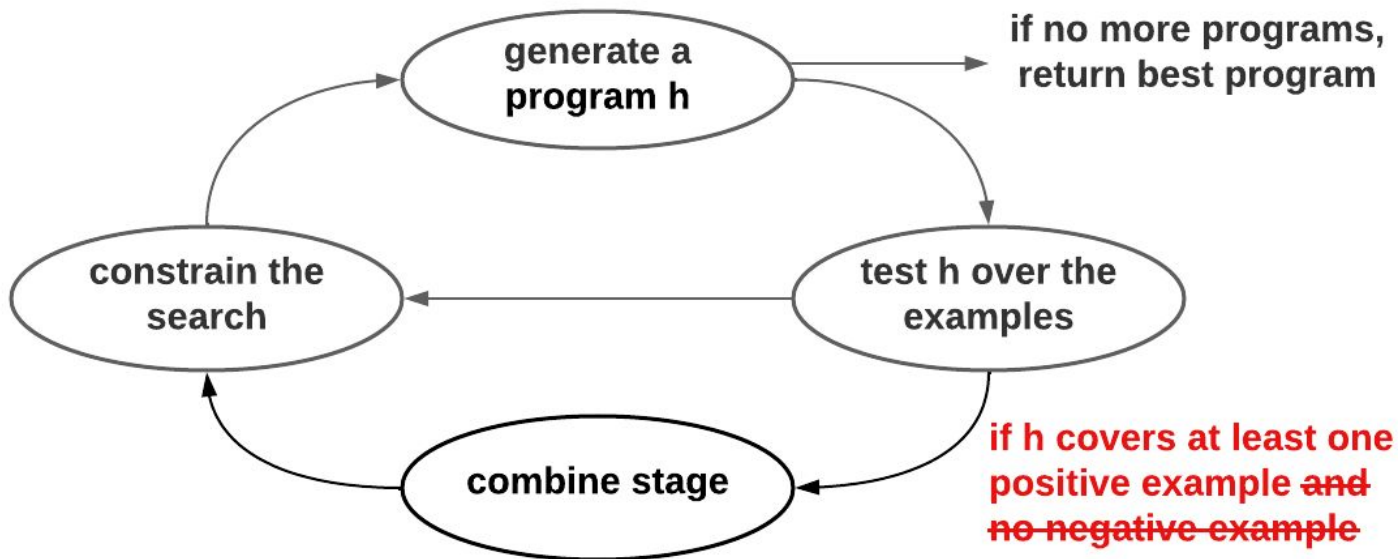
# Our cost function

minimum description length: trade-off model complexity (program size) and data fit (training accuracy)

$$mdl(h) = A size(h) + B fp(h) + C fn(h)$$

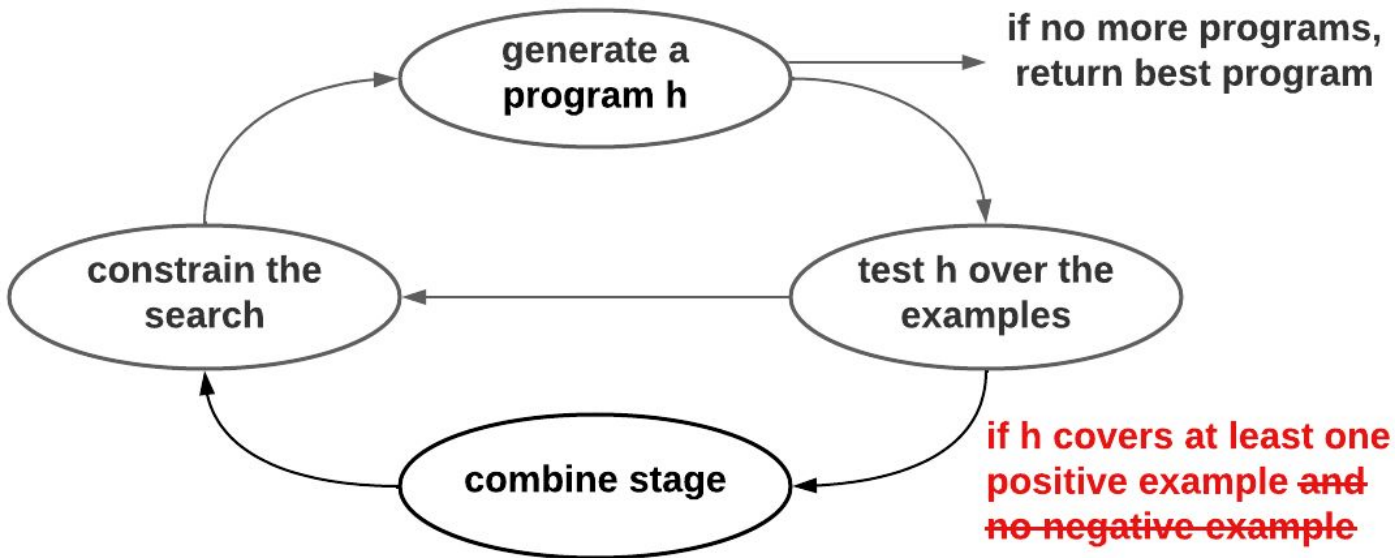
with  $A > 0$ ,  $B \geq 0$  and  $C \geq 0$

# Our approach





# Our approach



We use a MaxSAT solver to search for a MDL combination (a union) of programs.

# Implementation

We implement our approach in MaxSynth.

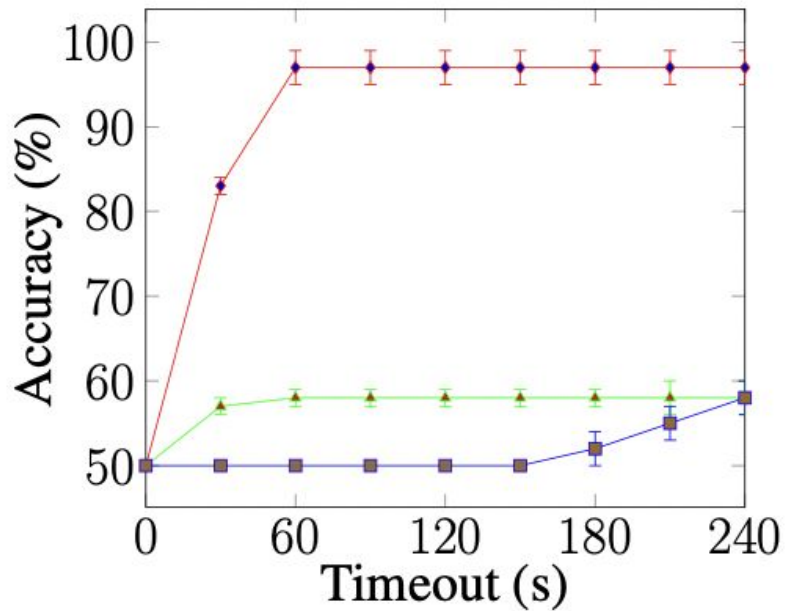
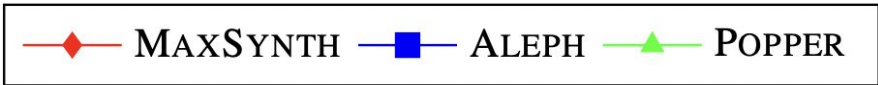
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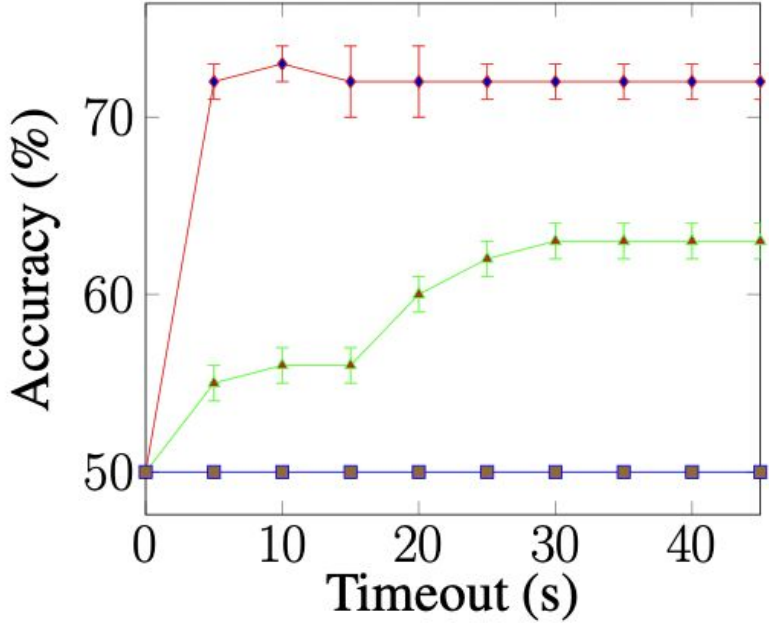
Theorem: MaxSynth learns an optimal solution (a MDL program) if one exists.

# Does it work?

**Q1** Can MAXSYNTH learn programs from noisy data?



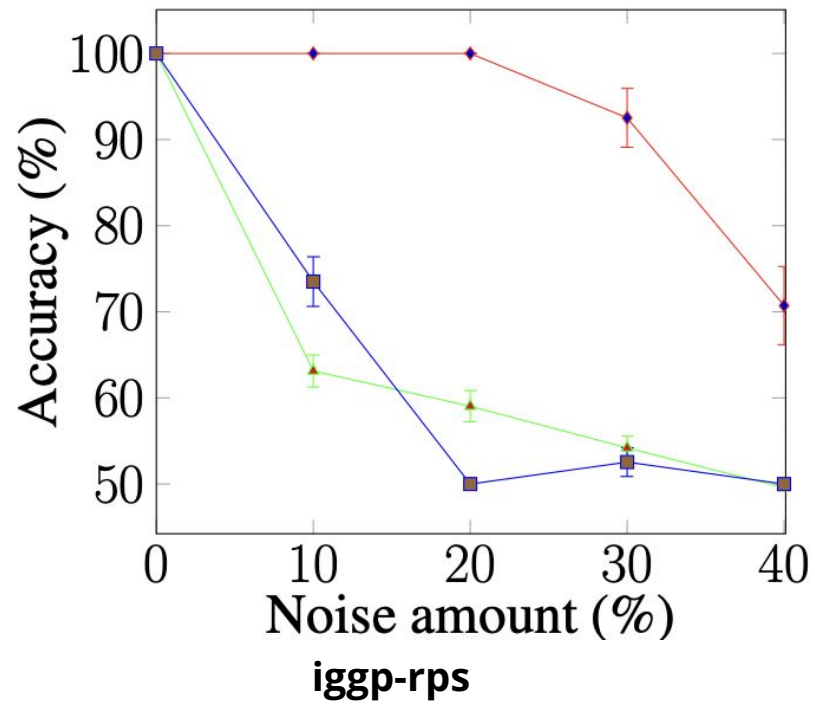
zendo



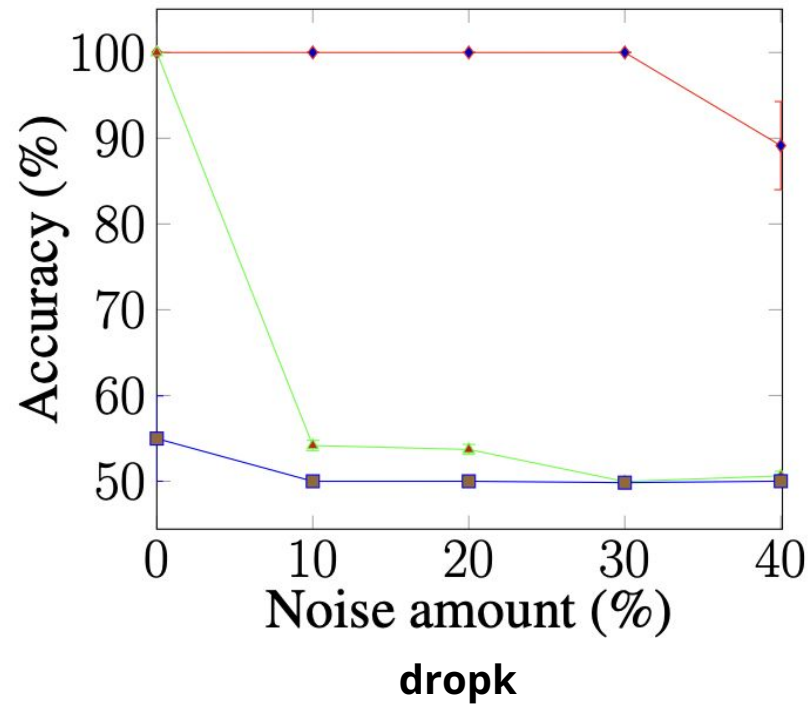
alzheimer-toxic

# Does it work?

**Q2** How well does MAXSYNTH handle progressively more noise?







# Conclusion

An approach that learns **minimal description length** programs from **noisy** examples.

Our approach can:

- improve learning performance,
- scale to moderate amount of noise.

# Limitation

- Cost function

$$mdl(h) = A \text{size}(h) + B \text{fp}(h) + C \text{fn}(h)$$

with  $A > 0$ ,  $B \geq 0$  and  $C \geq 0$

Thank you!

Questions?