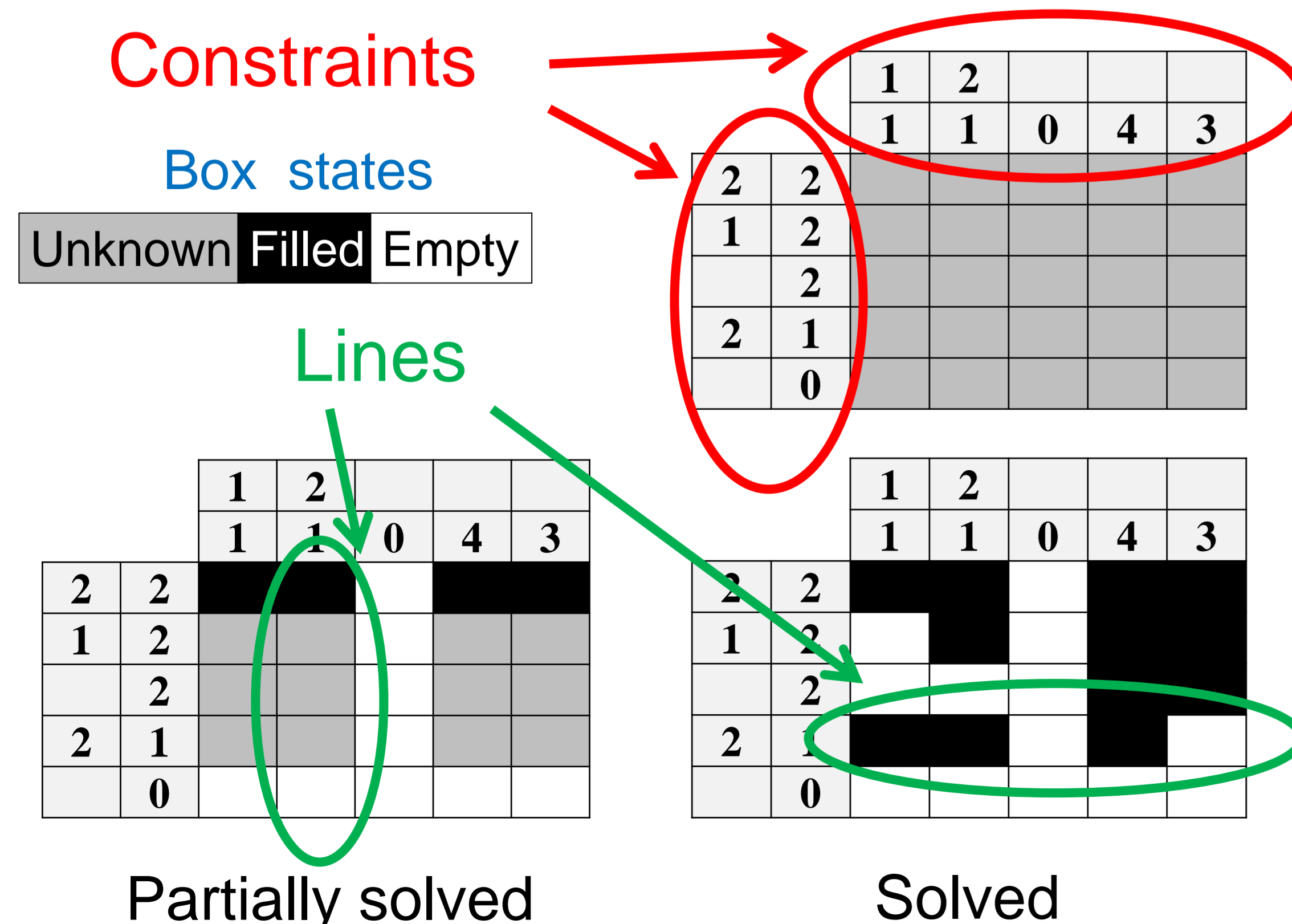


## Abstract

We study solvers of nonogram puzzles. Given an optimal solving module for solving a given line, we compare performance of three algorithmic solvers used to select the order in which to solve lines with reinforcement learning. The reinforcement-learning (RL) solver uses a measure of reduction of distance to goal as a reward. We compare two methods for storing qualities (Q values) of state-action pairs, a lookup table and a connectionist function approximator. We find that RL solvers learn near-optimal solutions that also outperform a heuristic solver based on explicit, general rules often given to nonogram players. Only RL solvers that use a connectionist function approximator generalize their knowledge to generate good solutions on about half of unseen problems; RL solvers based on lookup tables do not generalize.

## Nonogram puzzles



## Methods

1. Surveyed online nonogram web sites
2. Found two classes of advice
  - Solving a line: many explicit strategies and rules (e.g., Wikipedia, under Nonogram)
  - Selecting which line to solve: heuristic advice given for solved examples; few explicit rules

## Computational model

Hybrid system (explicit and implicit)

To **solve** a line: rule-based solver

To **select** lines: compare 4 solvers: Random, Heuristic, Optimal and Reinforcement learning

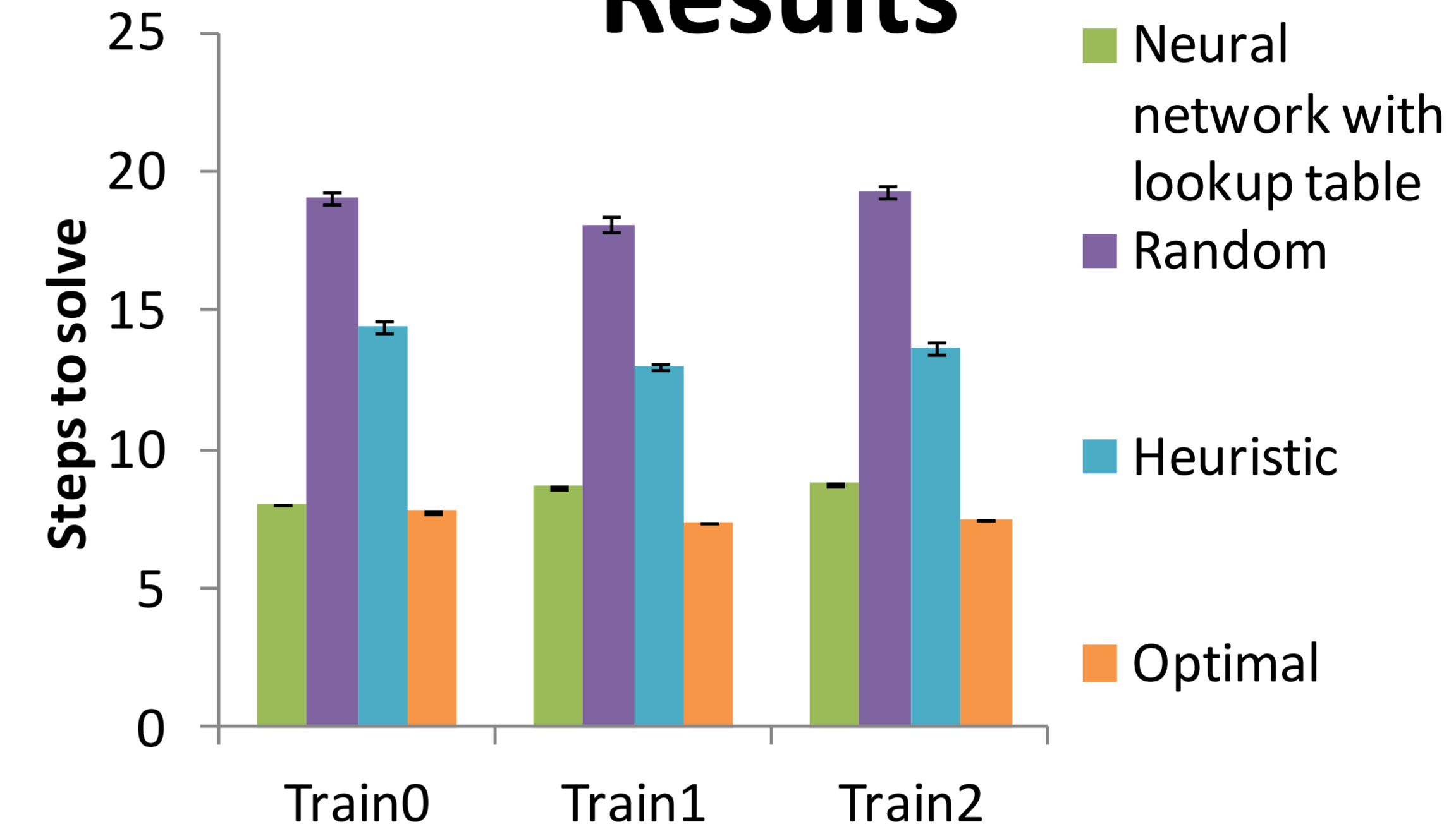
## Reinforcement-learning solver

- Learns expected value ( $Q$ ) of selecting this line ( $a_t$ ) in its present state ( $s_t$ )
- Higher reward ( $r_{t+1}$ ) for fewer steps

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

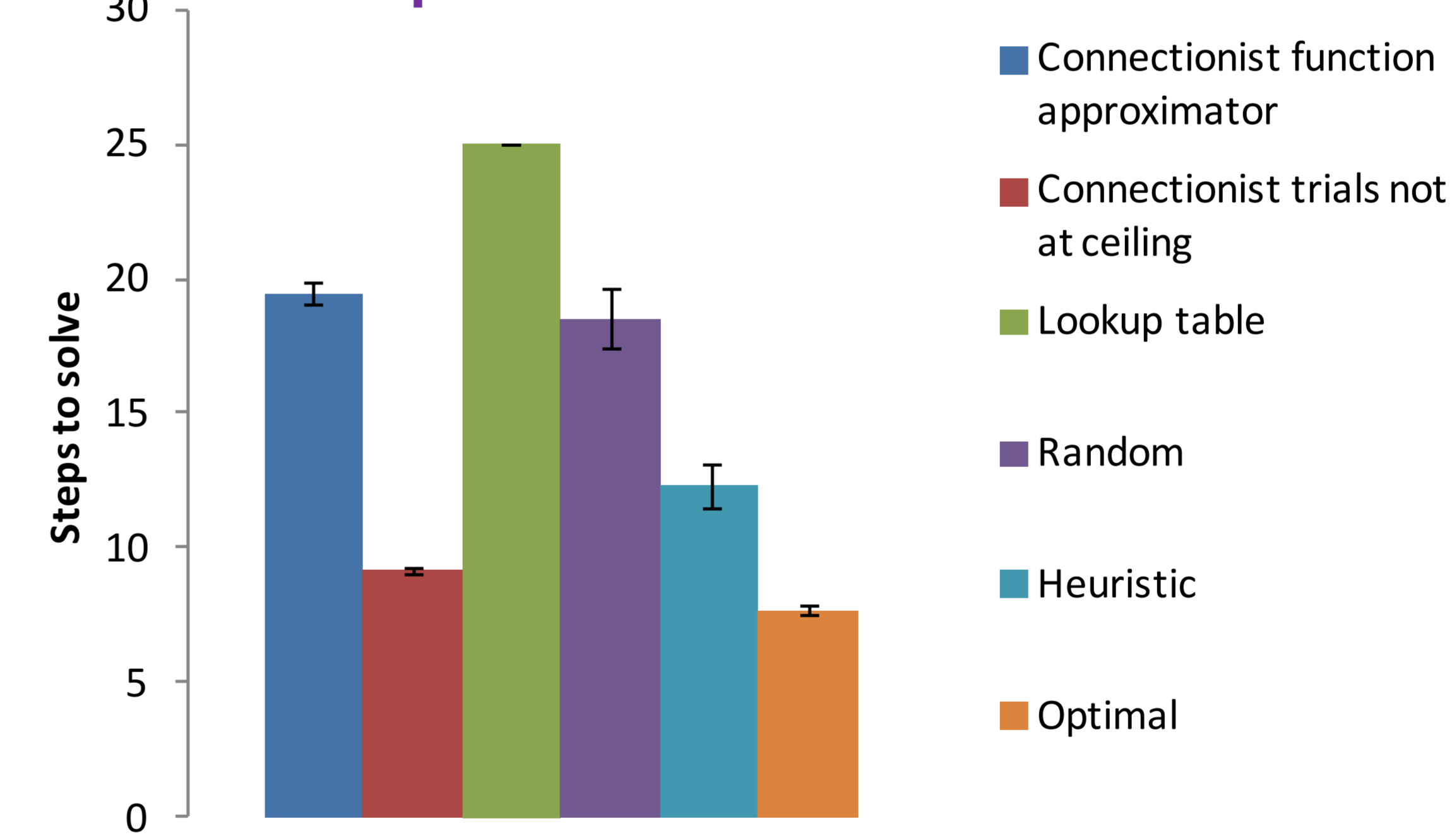
- Two methods for storing/computing  $Q$ 
  - (1) **Lookup table**
  - (2) Cascade-correlation **neural network** function approximator
- Inputs: concatenation of a line's current state and its constraints
- Output: predicted (estimated)  $Q$
- Training : 3 nonograms puzzles
- Testing: an unseen nonogram

## Results



## Generalization (testing set)

Lookup table vs. **Cascor neural network**



## Discussion

- Reinforcement-learning based model learns near-optimal performance
- On step 1, some correlation between heuristic and reinforcement-based solvers ( $r = 0.18$ ,  $p = 0.01$ )
- Generalization:

**Neural network > Lookup table**

## Future work

- Collect human data for cognitive modeling
- Develop a universal solver which works on any nonogram puzzle, of any size

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