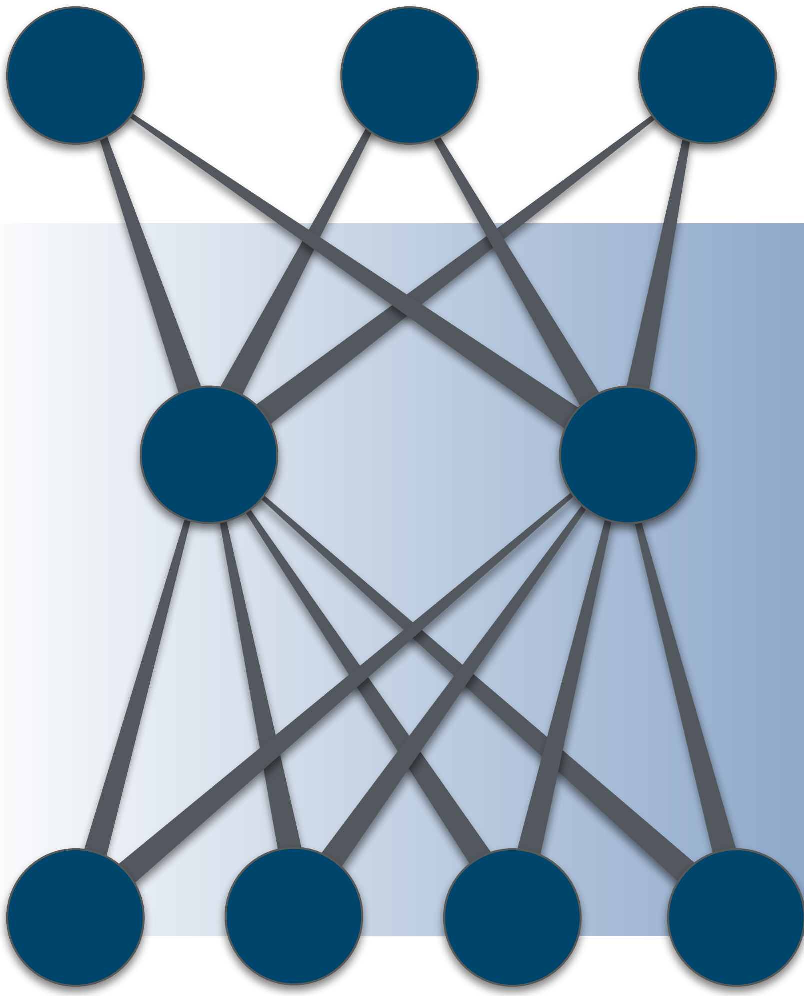

Comparing Direct and Indirect Encodings Using Both Raw and Hand-Designed Features in Tetris

By Lauren Gillespie, Gabby Gonzales and Jacob Schrum

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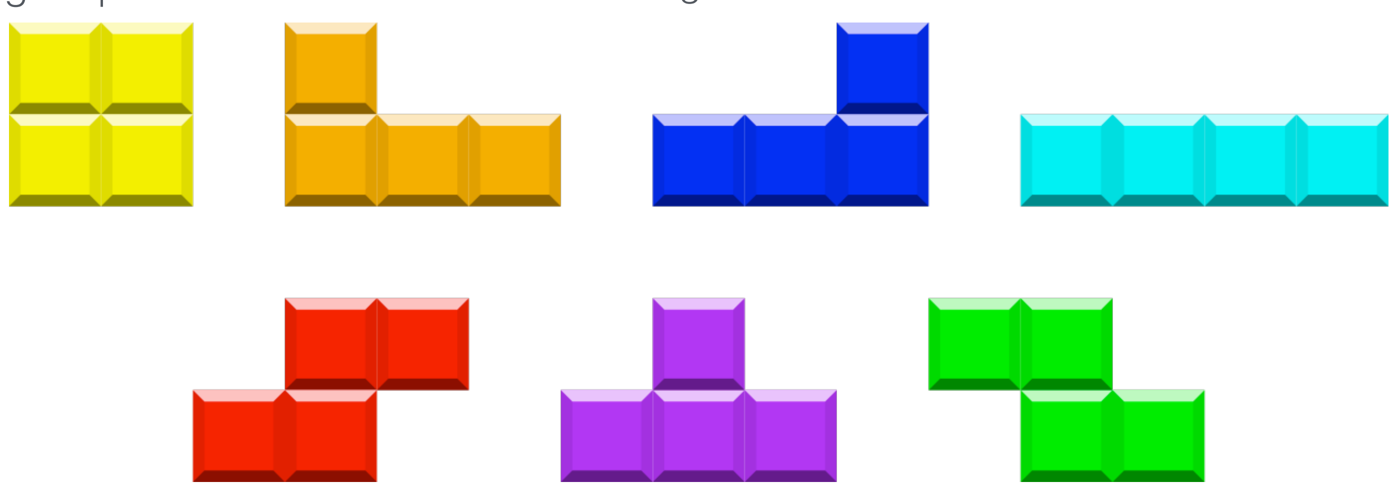

Southwestern University

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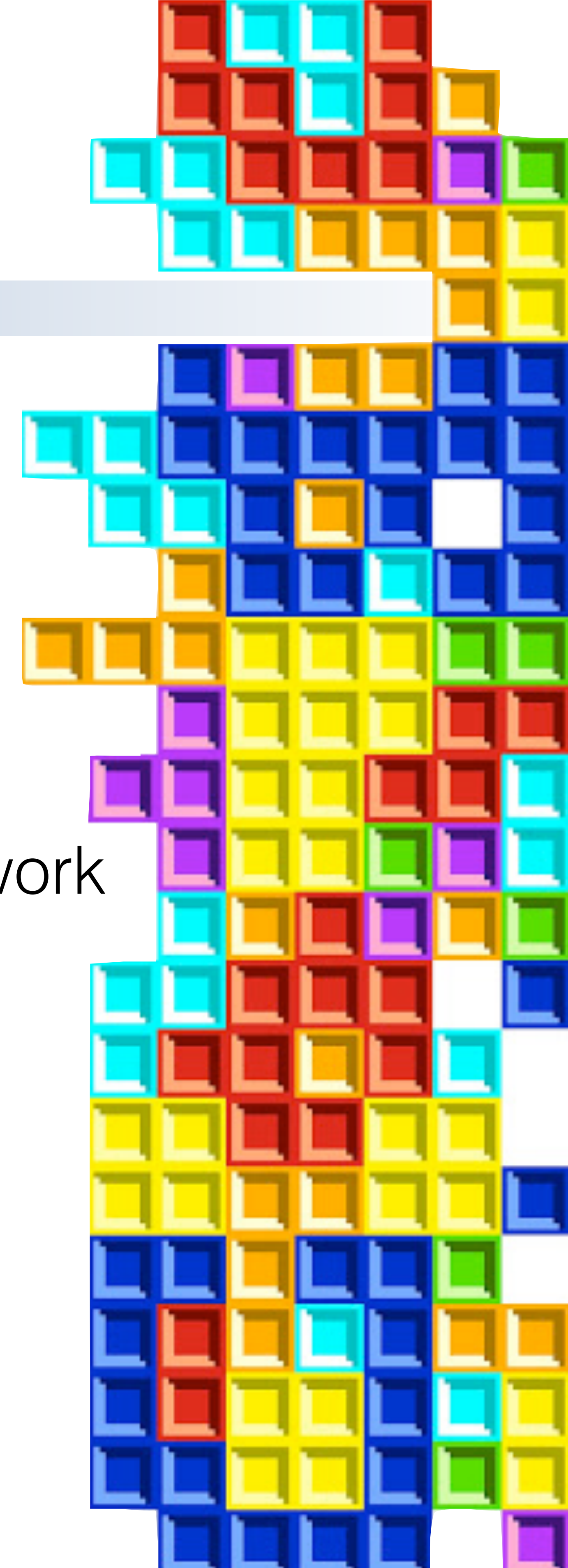
Introduction



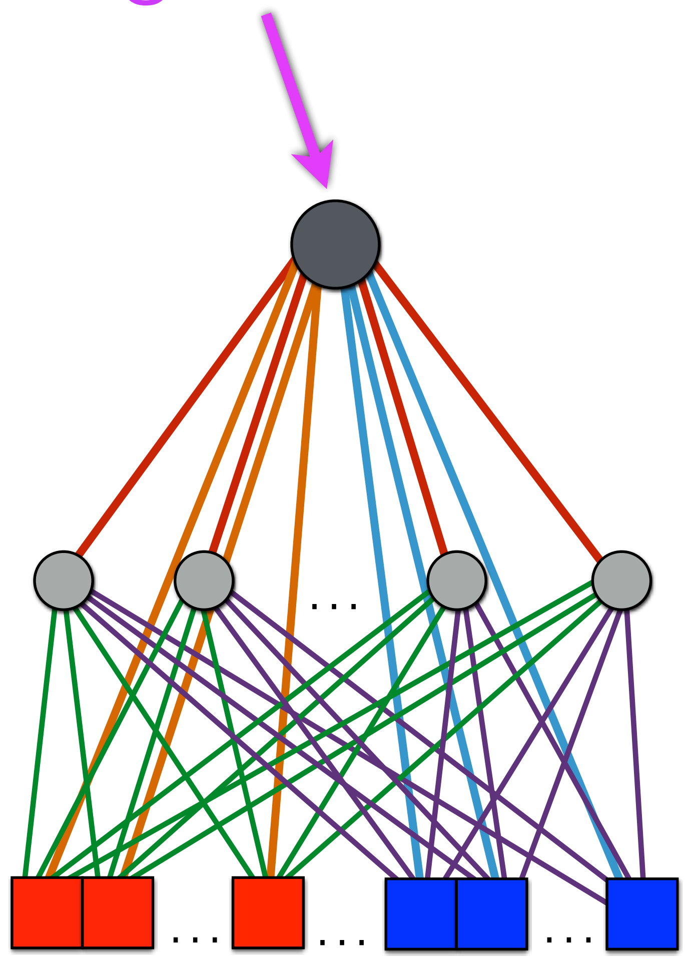
- Challenge: Use less domain-specific knowledge
    - Important for general agents
    - Accomplished using raw inputs
    - Need to be able to process with a neural network
- Why challenging?
    - Complex domains = Large input space
    - Large input space = Large neural networks
    - Large neural networks = Difficult to train

Addressing Challenges

- Deep Learning applies large NN to hard tasks[†]
- HyperNEAT also capable of handling large NNs
  - Indirect encoding, good with geometric inputs[‡]
  - Compare to direct encoding, NEAT
  - See if indirect encoding advantageous
  - Also compare with hand-designed features

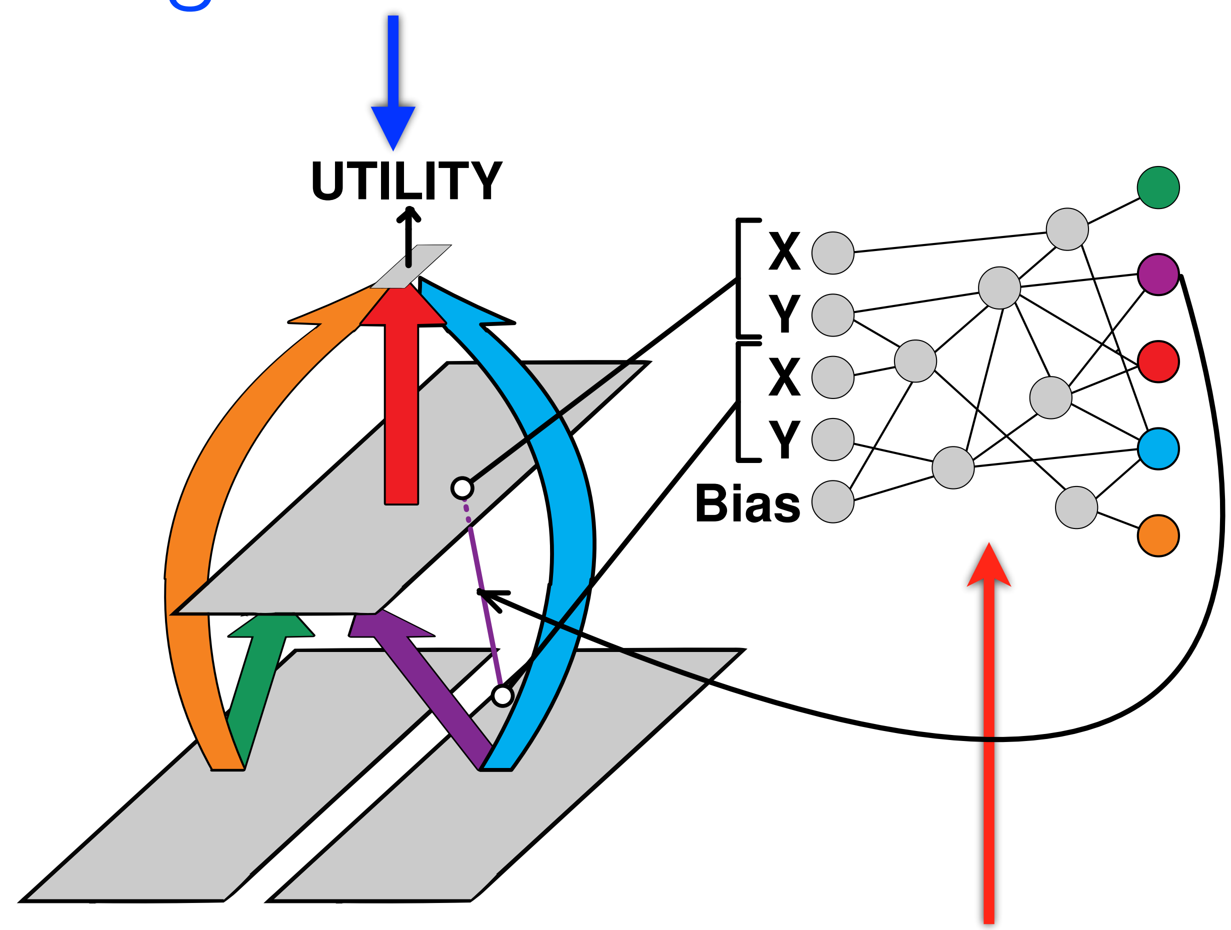
† Mnih et al. 2013. Playing Atari with Deep Reinforcement Learning.
‡Hausknecht et al. 2012. HyperNEAT-GGP: A HyperNEAT-based Atari General Game Player.

Direct Vs. Indirect Encoding



Direct Encoding

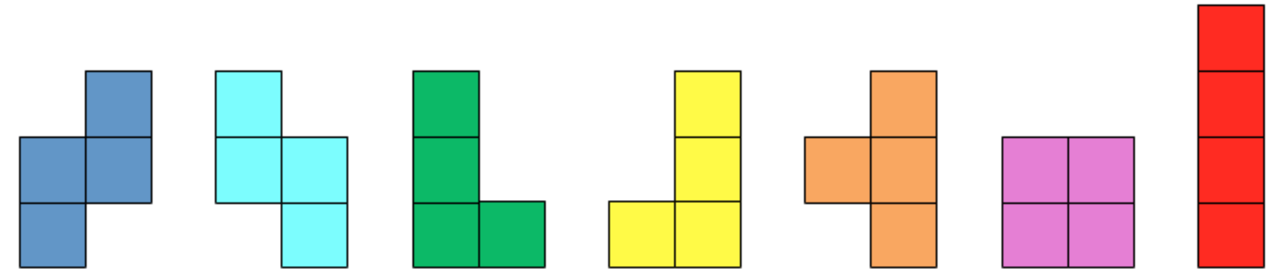
(NEAT)

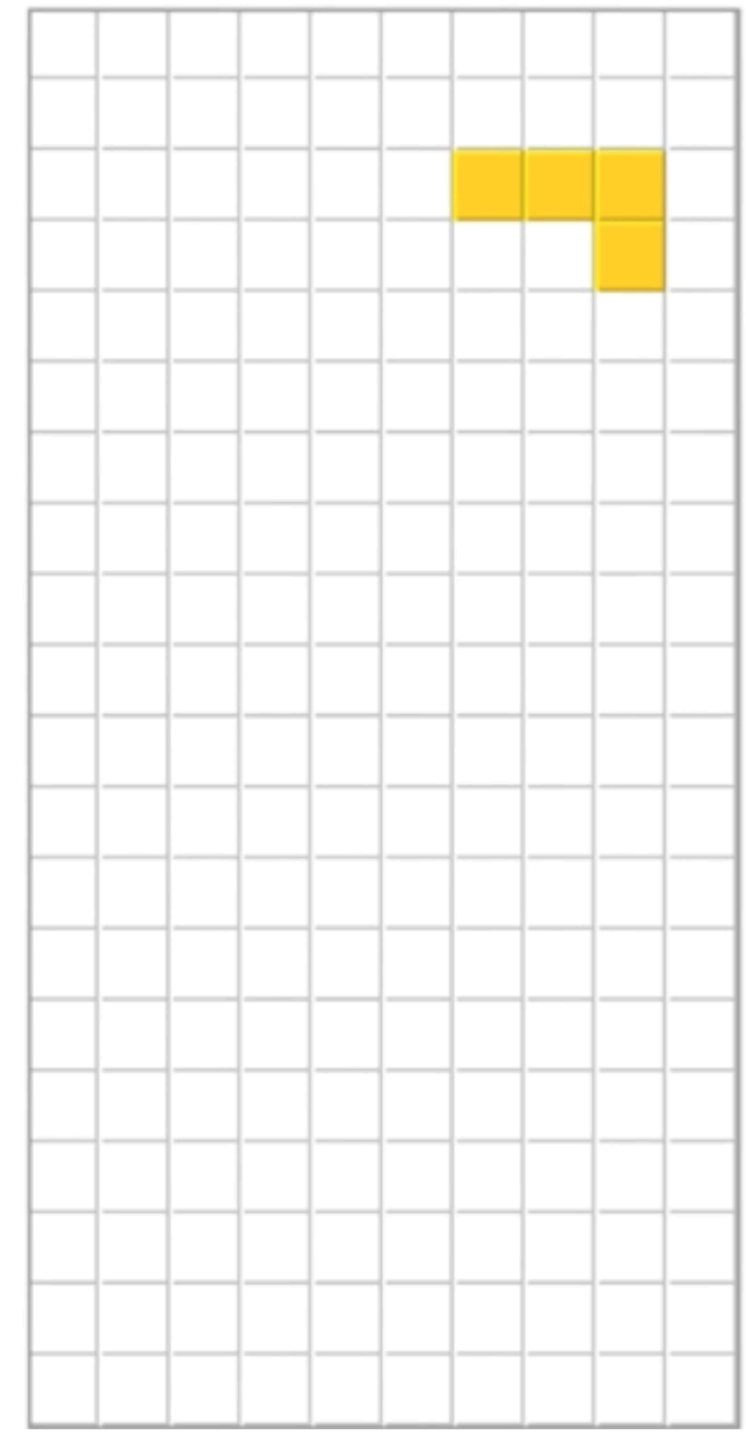


Indirect Encoding

(HyperNEAT)

Tetris Domain



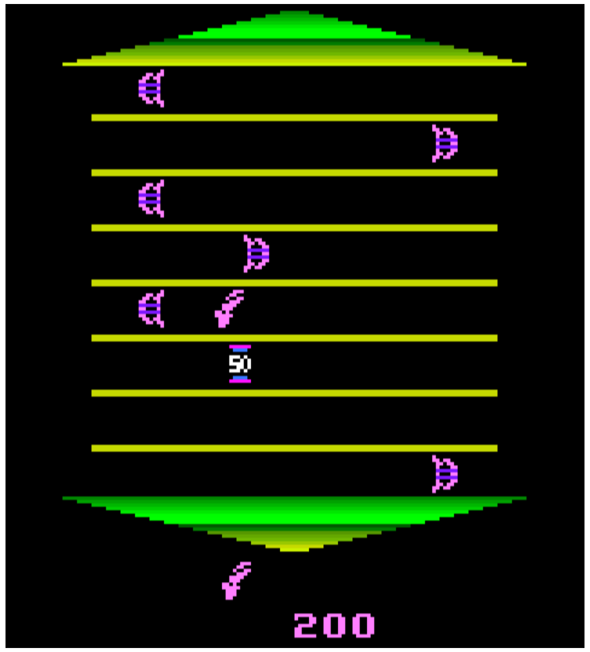


- Consists of 10 x 20 game board
- Orient tetrominoes to clear lines
- Clearing multiple lines = more points
- NP-Complete domain†
- One piece controller
  - Agent has knowledge of current piece only

† Breukelaar et al. 2004. Tetris is hard, even to approximate.

Previous Work

- Tetris Domain
  - All use hand-designed features
  - Reinforcement Learning:
    - Temporal difference learning: Bertsekas et al. 1996, Genesereth & Björnsson 2013
    - Policy search: Szitza & Lörincz 2006
    - Approximate Dynamic Programming: Gabillon et al. 2013
  - Evolutionary Computation:
    - Simple EA with linear function approximator: Böhm et al. 2004
    - Covariance Matrix Adaptation Evolution Strategy: Boumaza 2009
- Raw Visual Inputs
  - Neuroevolution: Gauci & Stanley 2008, Verbancsics & Stanley 2010
  - General video game playing in Atari: Hausknecht et al. 2012, Mnih et al. 2013



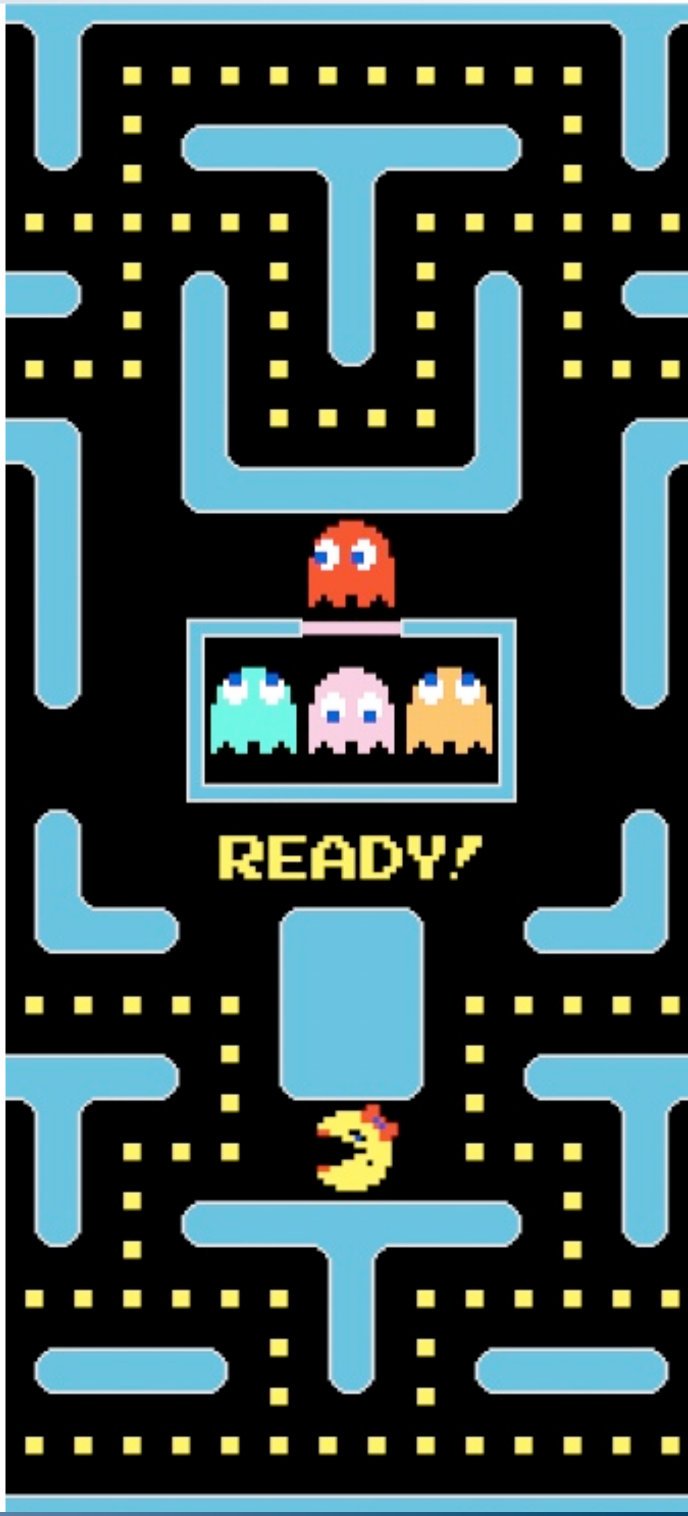
Asterix game from Atari 2600 Suite

Hand-Designed Features

- Most common input scheme for training ANNs†
- Hand-picked information of game state as input

Pros:
- ✦ Network doesn't deal with excess info
- ✦ Smaller input space, easier to learn

Cons:
- ✦ Very domain-specific, not versatile
- ✦ Human expertise needed
- ✦ Useful features not always apparent



† Schrum & Miikkulainen. 2016. Discovering Multimodal Behavior in Ms. Pac-Man through Evolution of Modular Neural Networks.

Raw Features

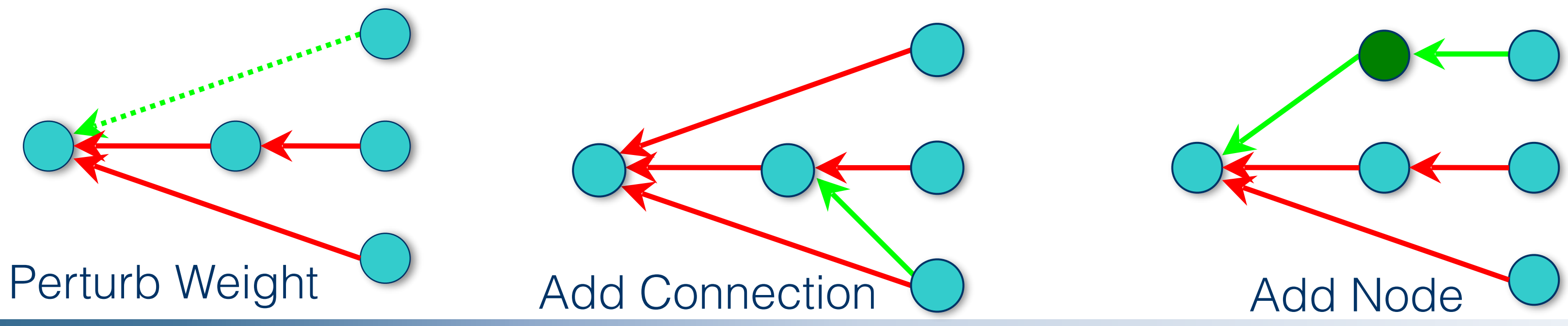
- One feature per game state element
- Minimal input processing by user

Pros:
- ✦ Networks less limited by domain†
- ✦ Less human expertise needed

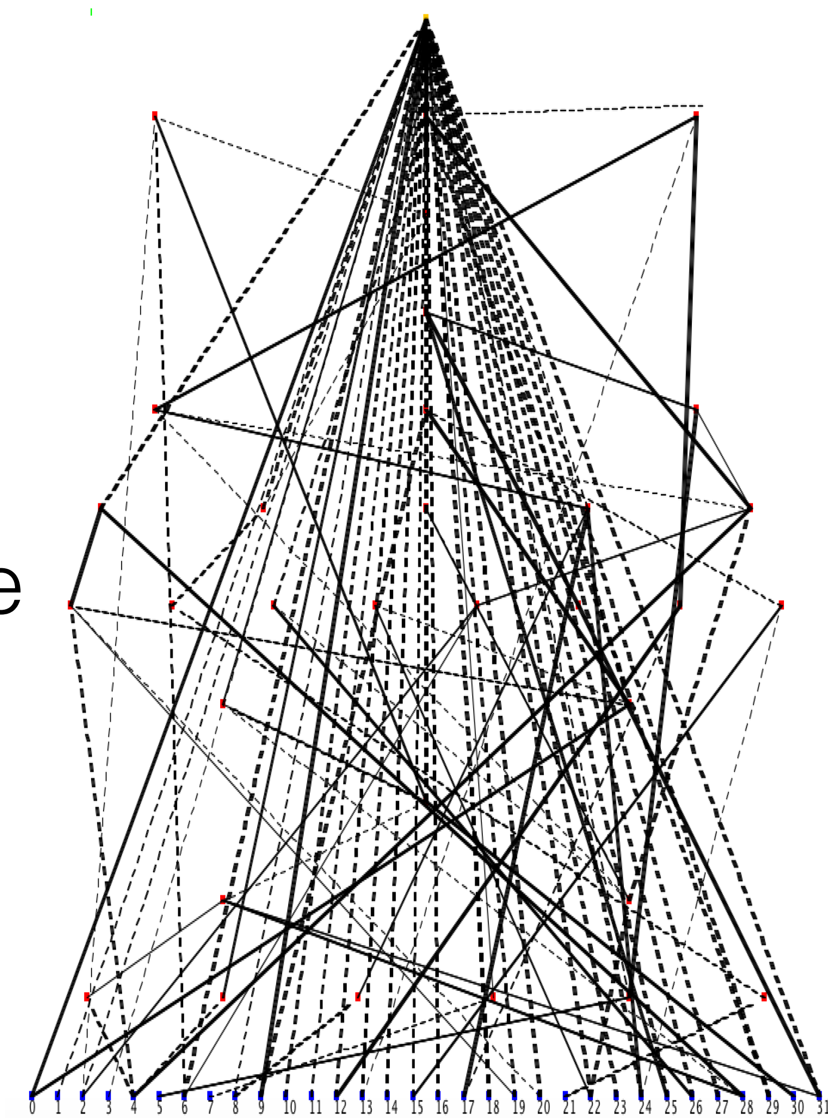
Cons:
- ✦ Large input space & networks
- ✦ Harder to learn, more time

† Gauci & Stanley. 2008. A Case Study on the Critical Role of Geometric Regularity in Machine Learning.

NEAT

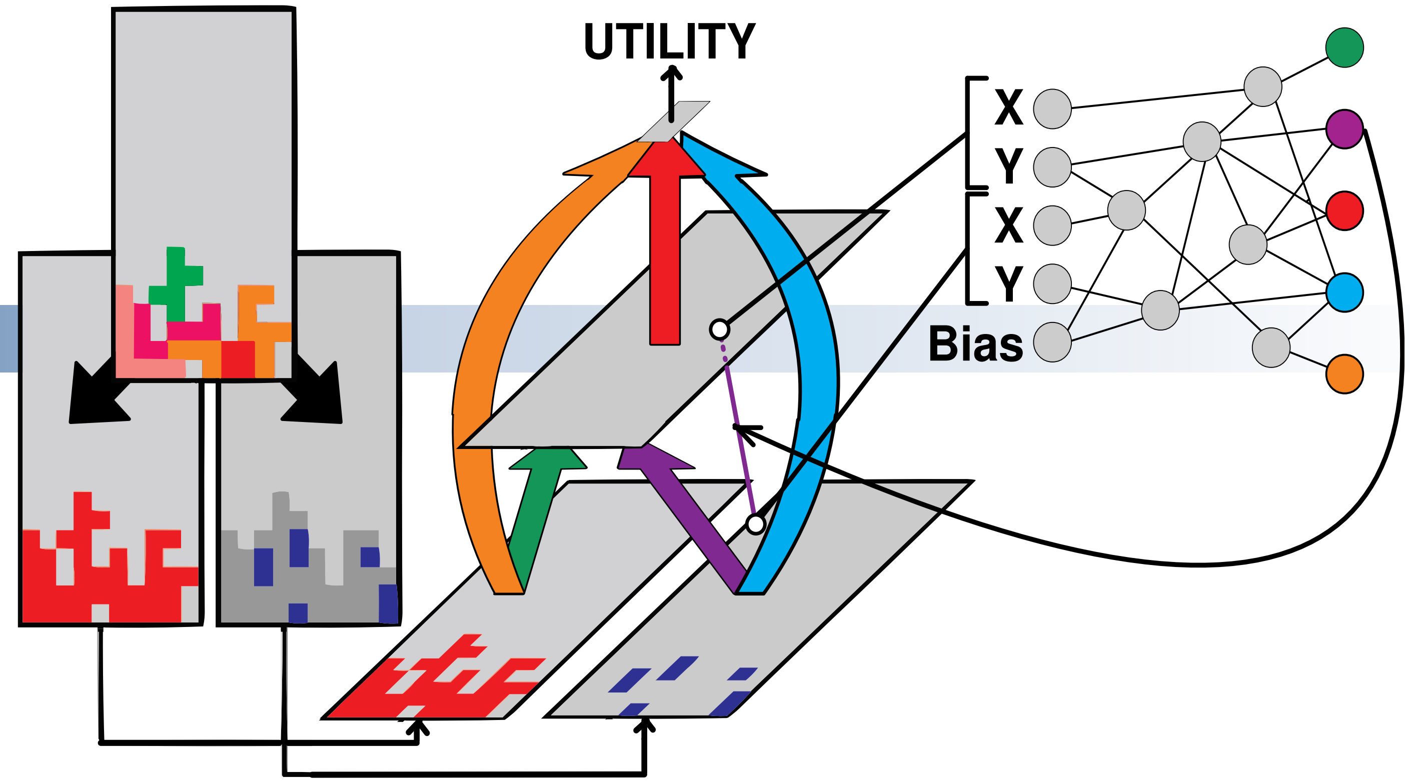


- NeuroEvolution of Augmenting Topologies†
- Synaptic and structural mutations
- Direct encoding
  - Network size proportional to genome size
- Crossover alignment via historical markings
- Inefficient with large input sets
  - Mutations do not alter behavior effectively



† Stanley & Miikkulainen. 2002. Evolving Neural Networks Through Augmenting Topologies

HyperNEAT

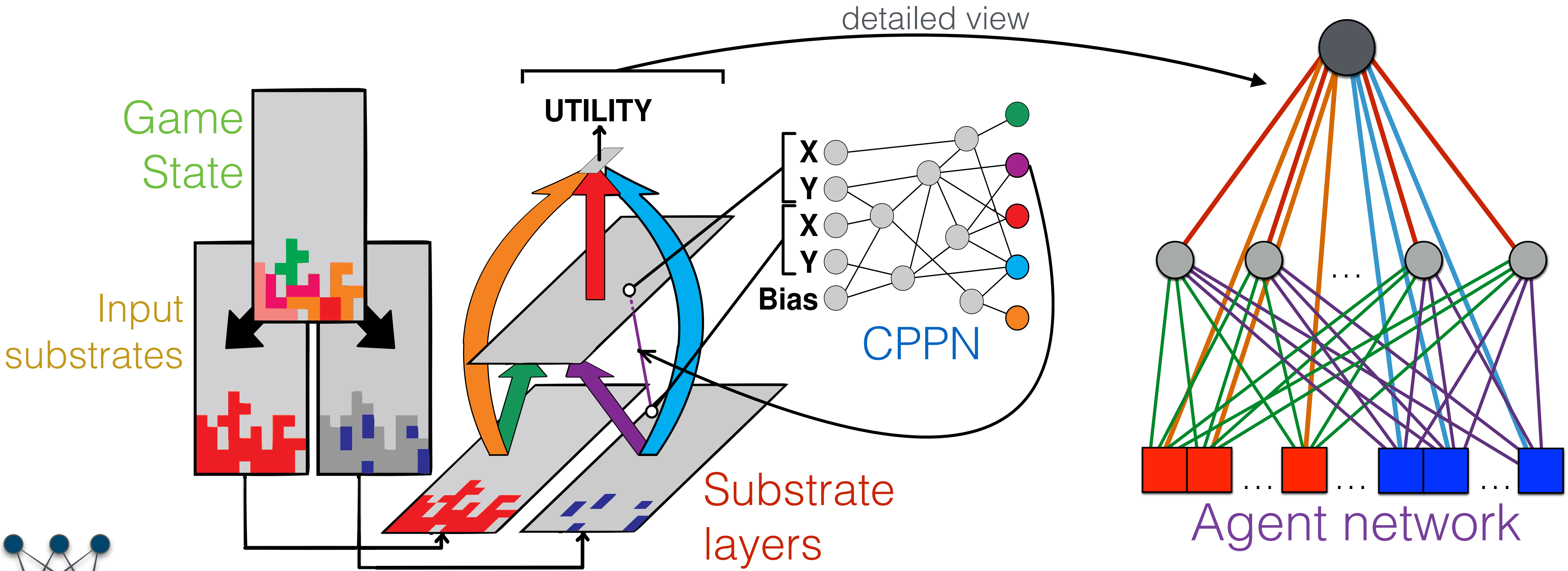


- Hypercube-based NEAT[†]
- Extension of NEAT
- Indirect encoding
    - ✦ Evolved CPPNs encode larger substrate-based agent ANNs
- Compositional Pattern-Producing Networks (CPPNs)
    - ✦ CPPN queried across substrate to create agent ANN
    - ✦ Inputs = neuron coordinates, outputs = link weights
- Substrates
    - ✦ Layers of neurons with geometric coordinates
    - ✦ Substrate layout determined by domain/experimenter

† Stanley et al. 2009. A Hypercube- based Encoding for Evolving Large-scale Neural Networks

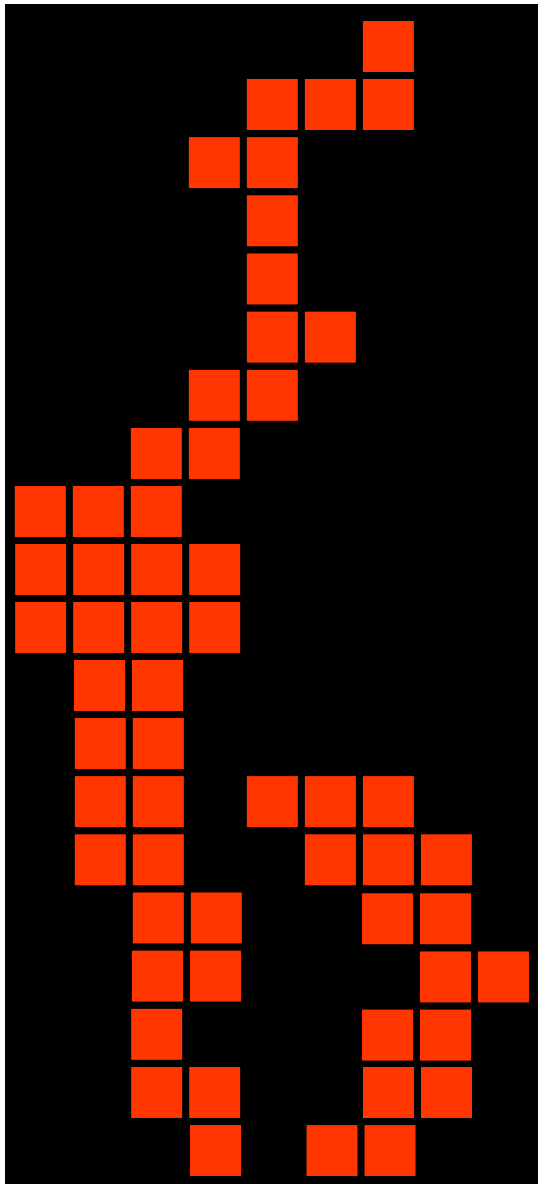
HyperNEAT with Tetris

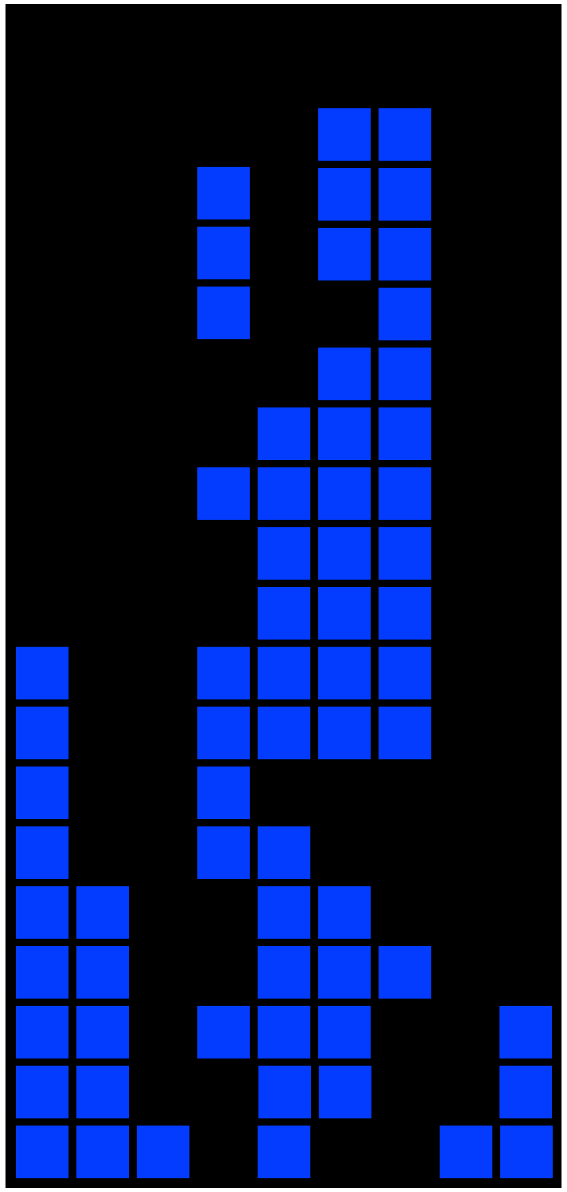
- *Geometric awareness*: arises from indirect encoding
- CPPN encodes geometry of domain into agent via substrates
- Agent network can learn from task-relevant domain geometry



Raw Features Setup

- Board configuration:
  - Two input sets
    1. Location of all blocks
       - block = 1, no block = 0
    2. Location of all holes
       - hole = -1, no hole = 0
- NEAT: Inputs in linear sequence
- HyperNEAT: Two 2D input substrates





Hand-Designed Features Setup

- Bertsekas et al. features† plus additional hole per column feature
- All scaled to [0,1]

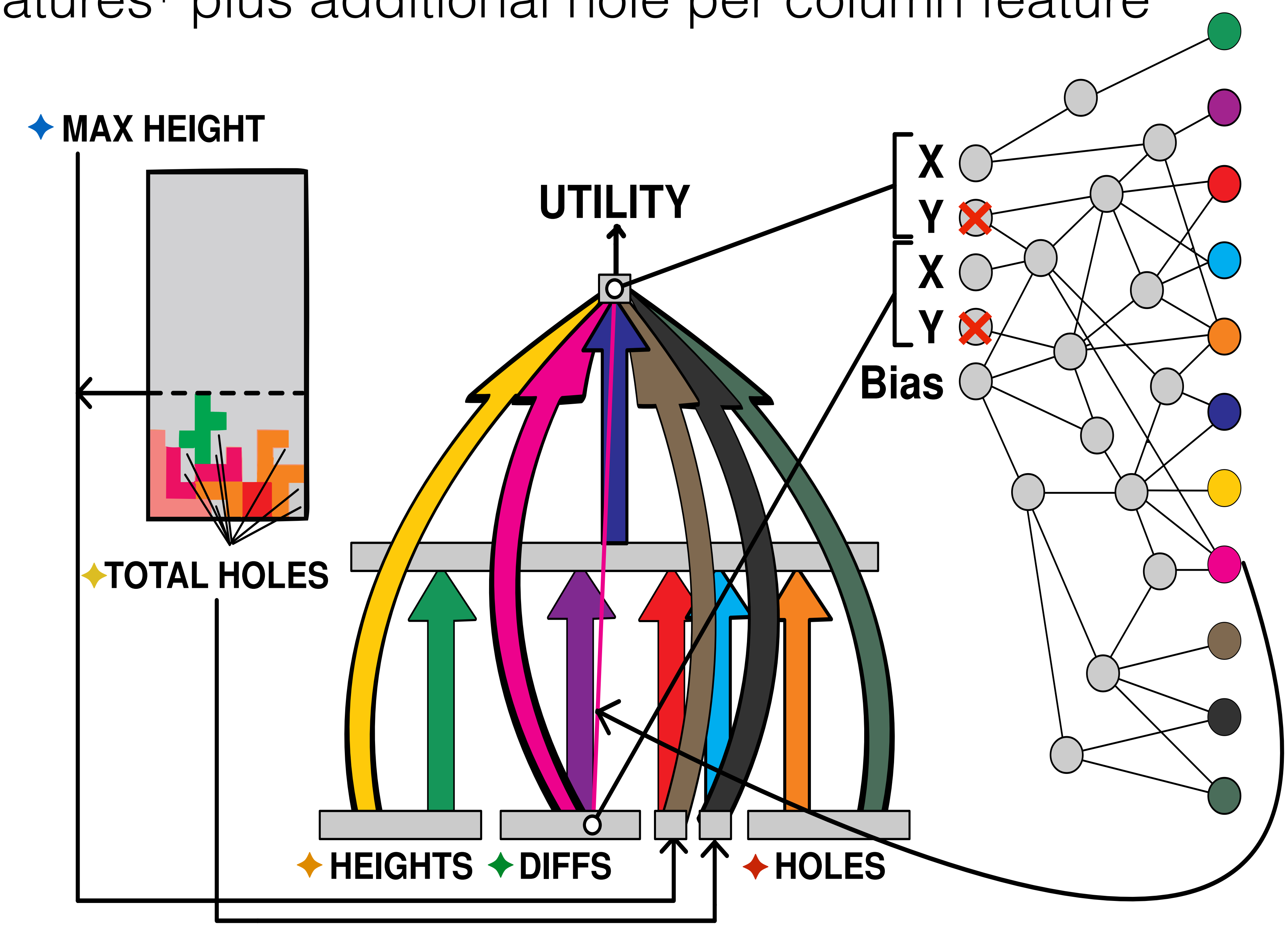
✦ Column height

✦ Height difference

✦ Tallest column

✦ Number of holes

✦ Holes per column

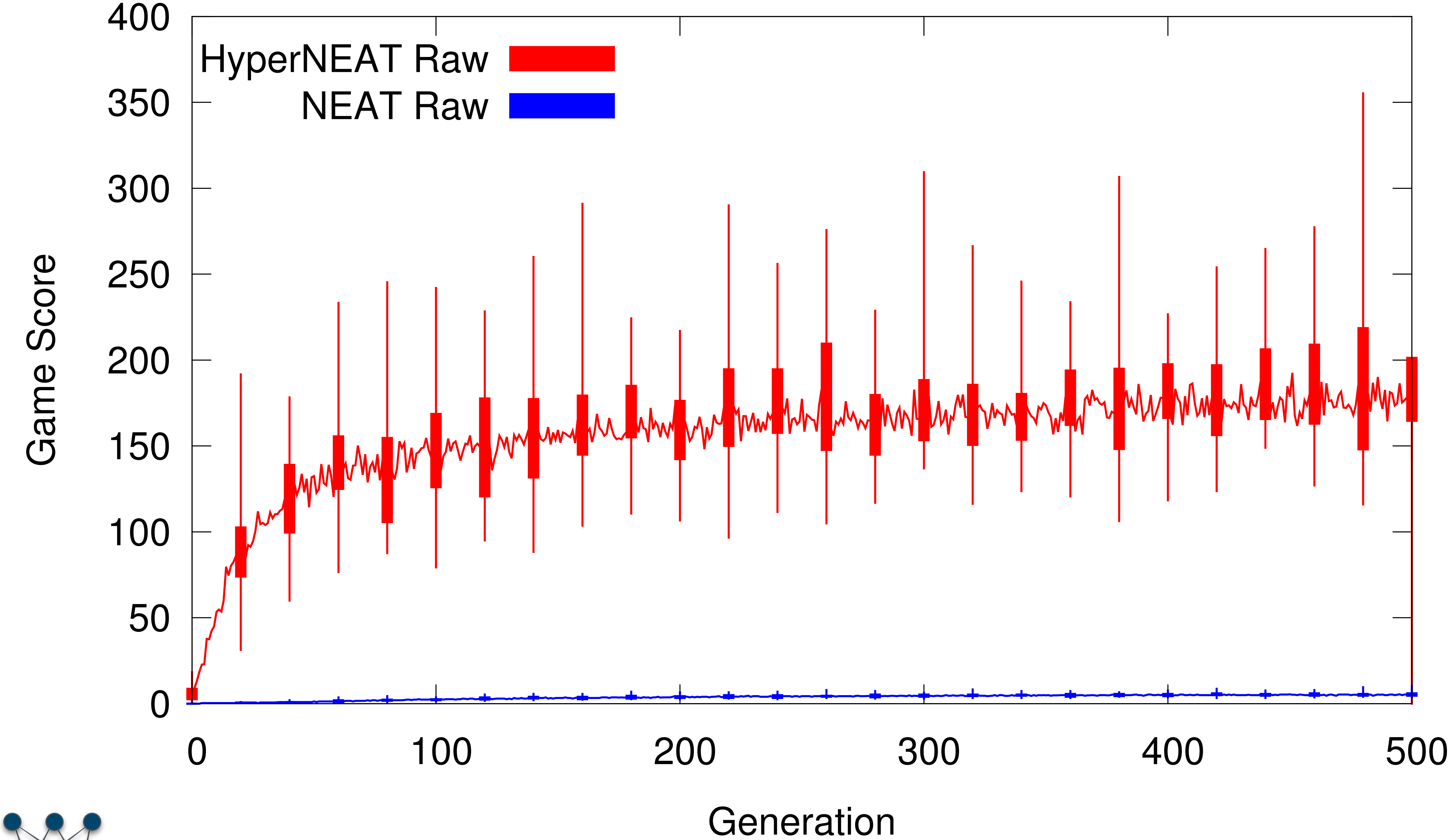


† Bersekas et al. 1996. Neuro-Dynamic Programming

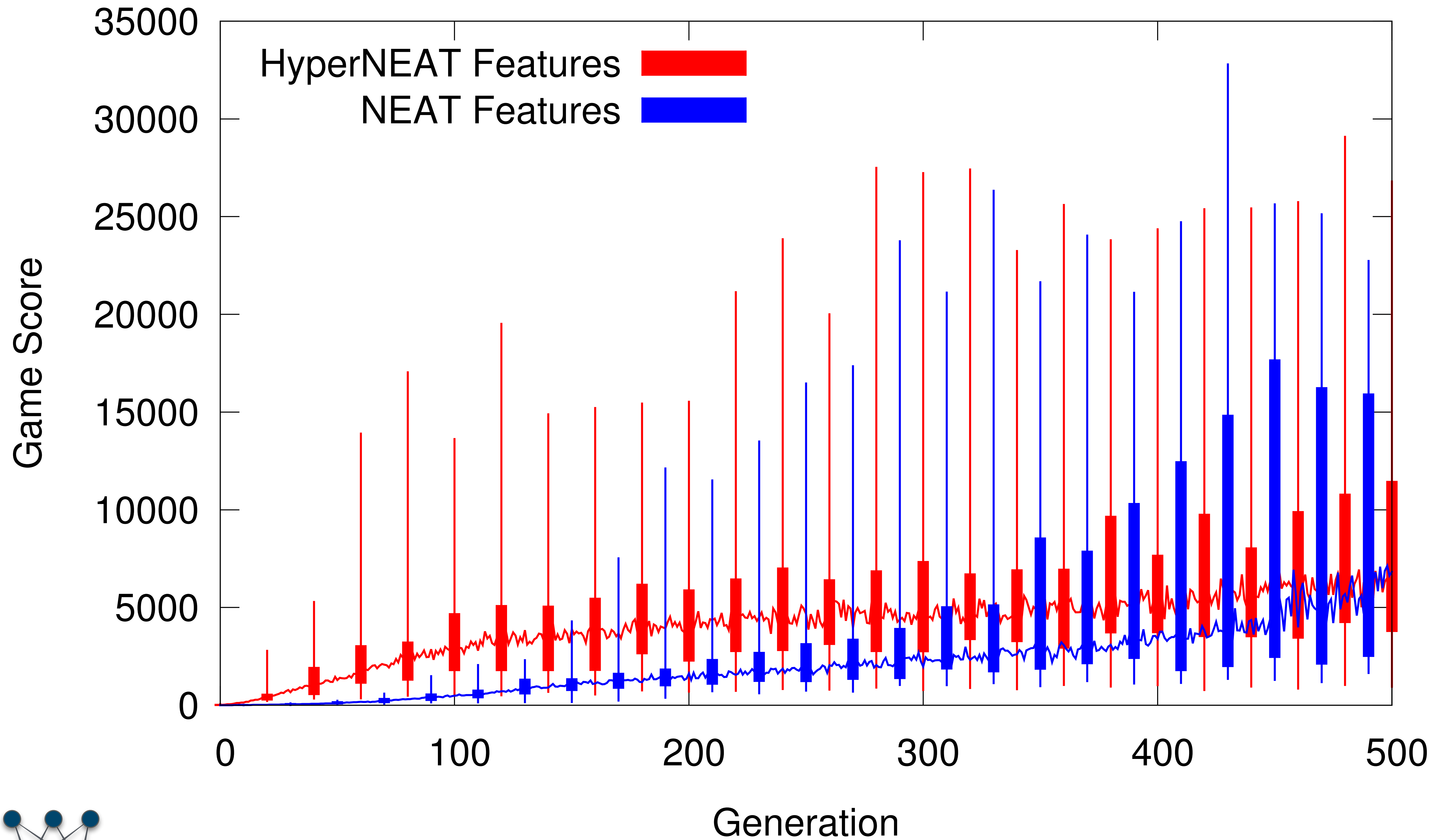
Experimental Setup

- Agent networks are afterstate evaluators
- Each experiment evaluated with 30 runs
  - 500 generations/run, 50 agents/generation
  - Objectives averaged across 3 trials/agent
    - Noisy domain, multiple trials needed
- NSGA-II objectives: game score & survival time

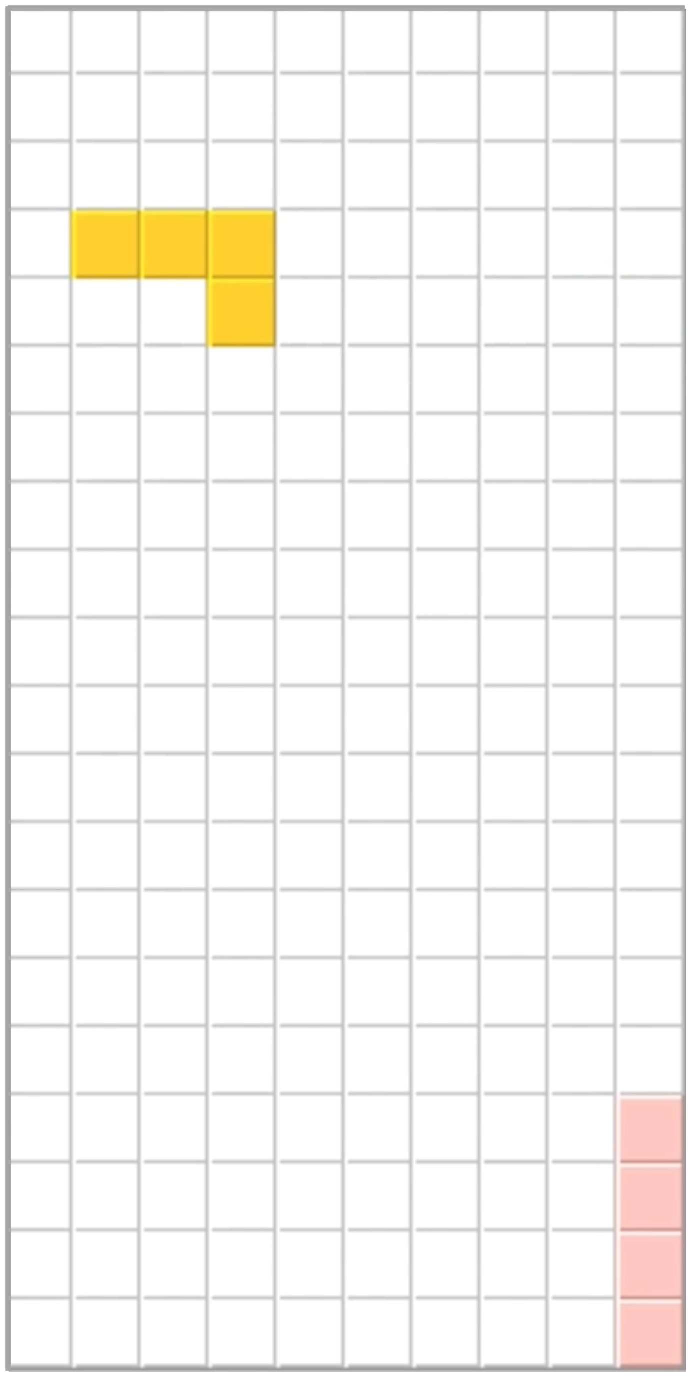
NEAT vs. HyperNEAT: Raw Features



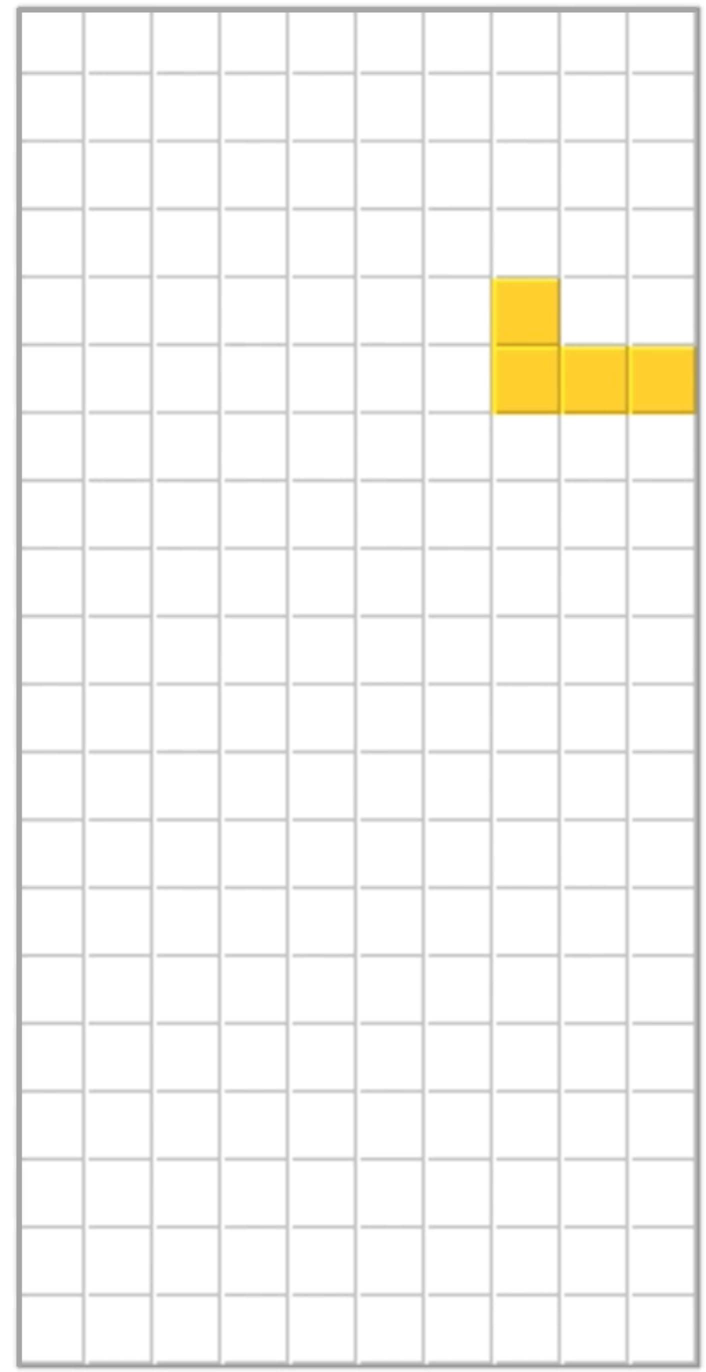
NEAT vs. HyperNEAT: Hand-Designed Features



Raw Features Champion Behavior



NEAT with Raw Features



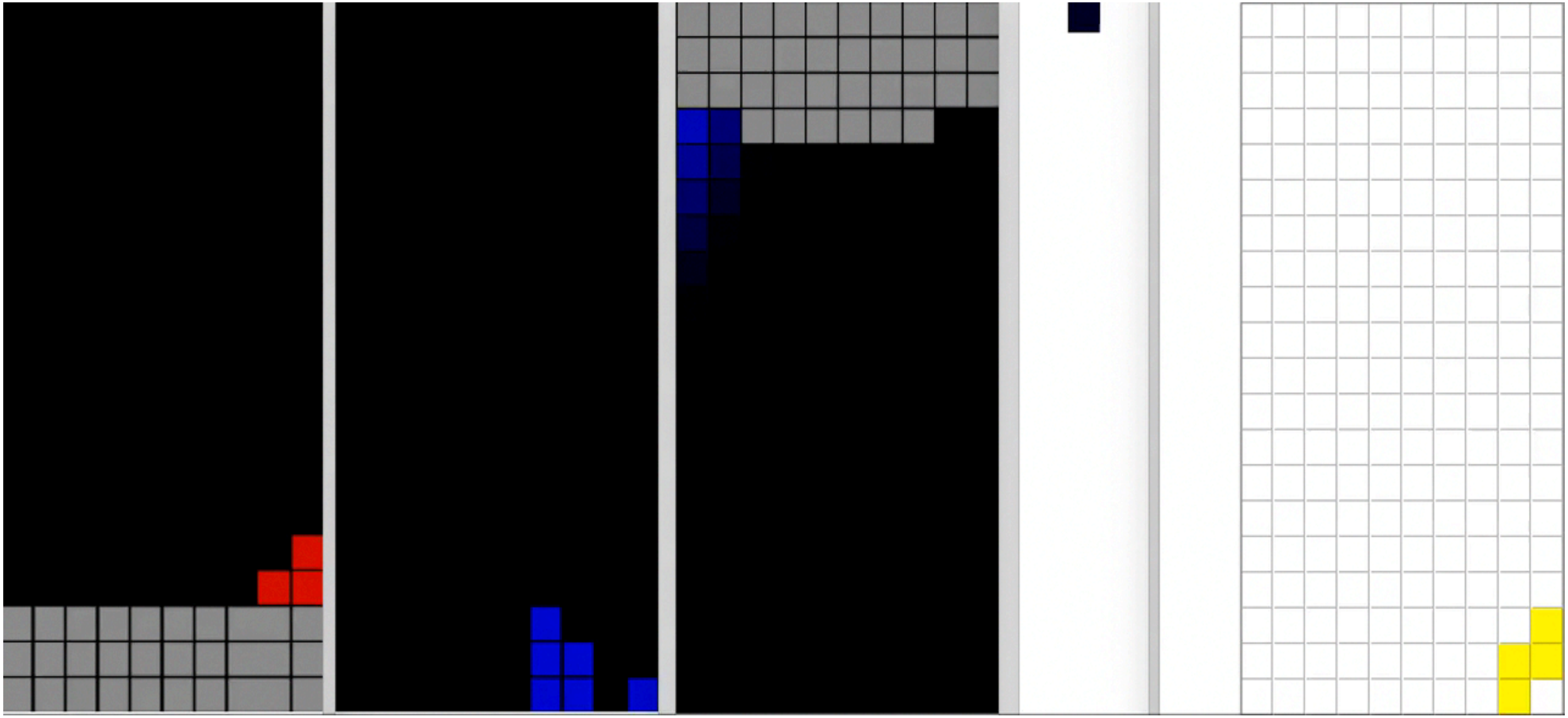
HyperNEAT with Raw Features

Hand-Designed Features Behavior

NEAT with Hand-Designed Features

HyperNEAT with Hand-Designed Features

Visualizing Substrates



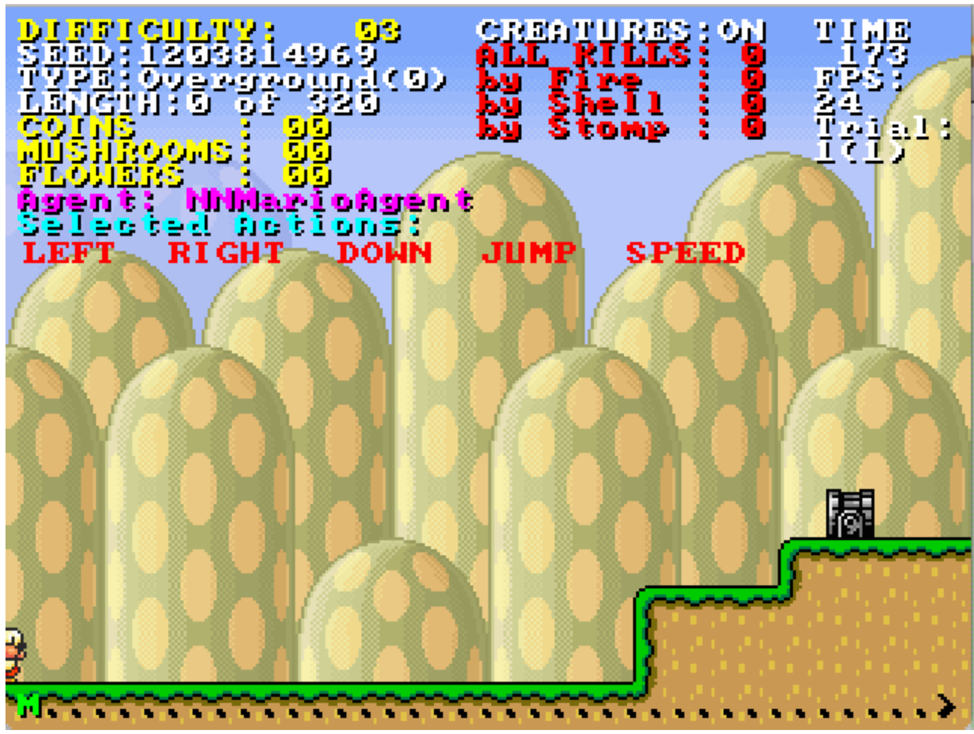
Inputs Hidden Output Result

Discussion

- Raw features: HyperNEAT clearly better than NEAT
    - Indirect encoding advantageous
    - NEAT ineffective at evolving large networks
- Hand-Designed: HyperNEAT has less of an advantage
    - Geometric awareness less important
    - HyperNEAT CPPN limited by substrate topology

Future Work

- HybrID†
  - ✦ Start with HyperNEAT, switch to NEAT
  - ✦ Gain advantage of both encodings
- Raw feature Tetris with Deep Learning
- Raw features in other visual domains
  - ✦ Video games: DOOM, Mario, Ms. Pac-Man
  - ✦ Board games: Othello, Checkers



† Clune et al. 2004. HybrID: A Hybridization of Indirect and Direct Encodings for Evolutionary Computation.

Conclusion

- Raw features
  - Indirect encoding HyperNEAT effective
  - Geometric awareness an advantage
- Hand-designed features
  - Ultimately NEAT produced better agents
  - HybrID might combine strengths of both

Questions?

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- Movies and Code:

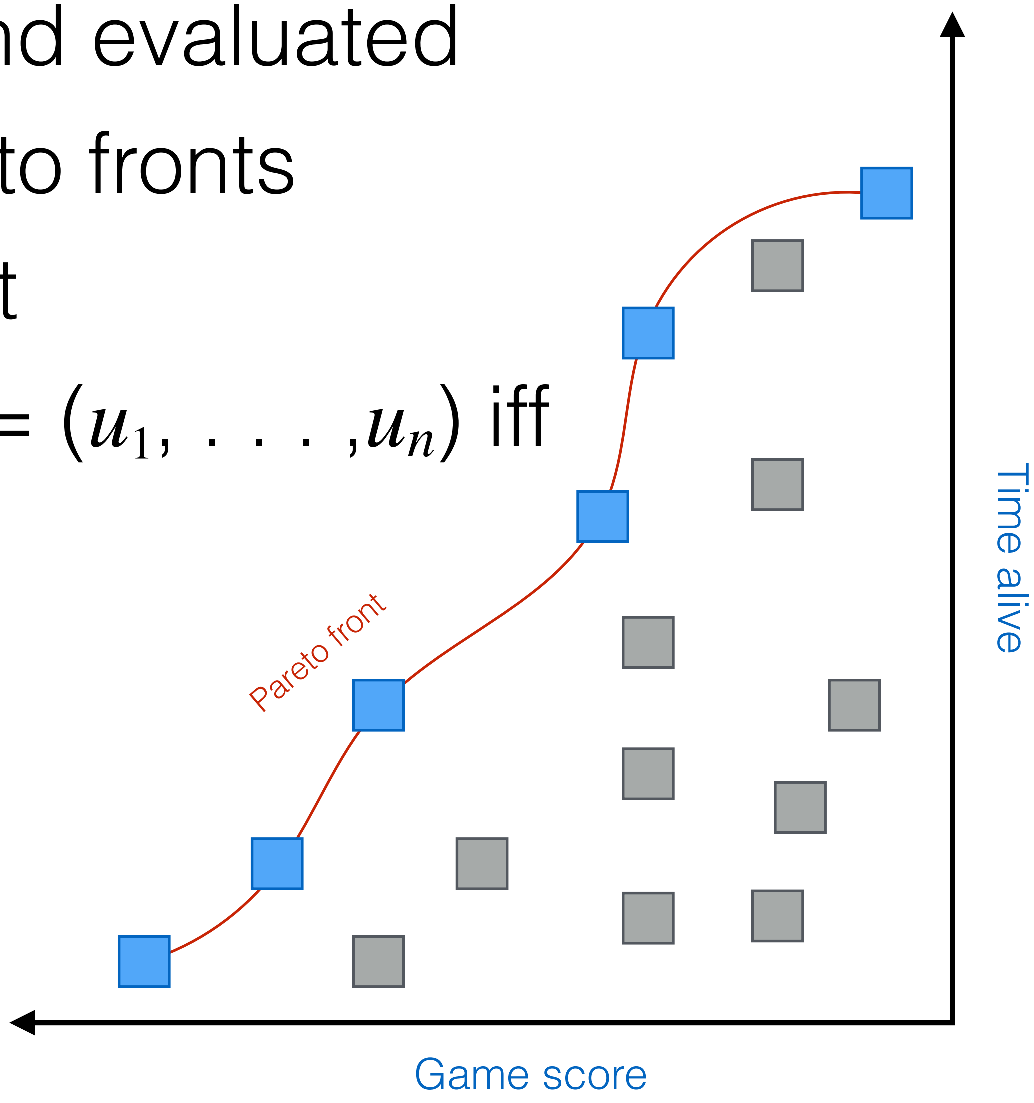
  https://tinyurl.com/tetris-gecco2017

Auxiliary Slides

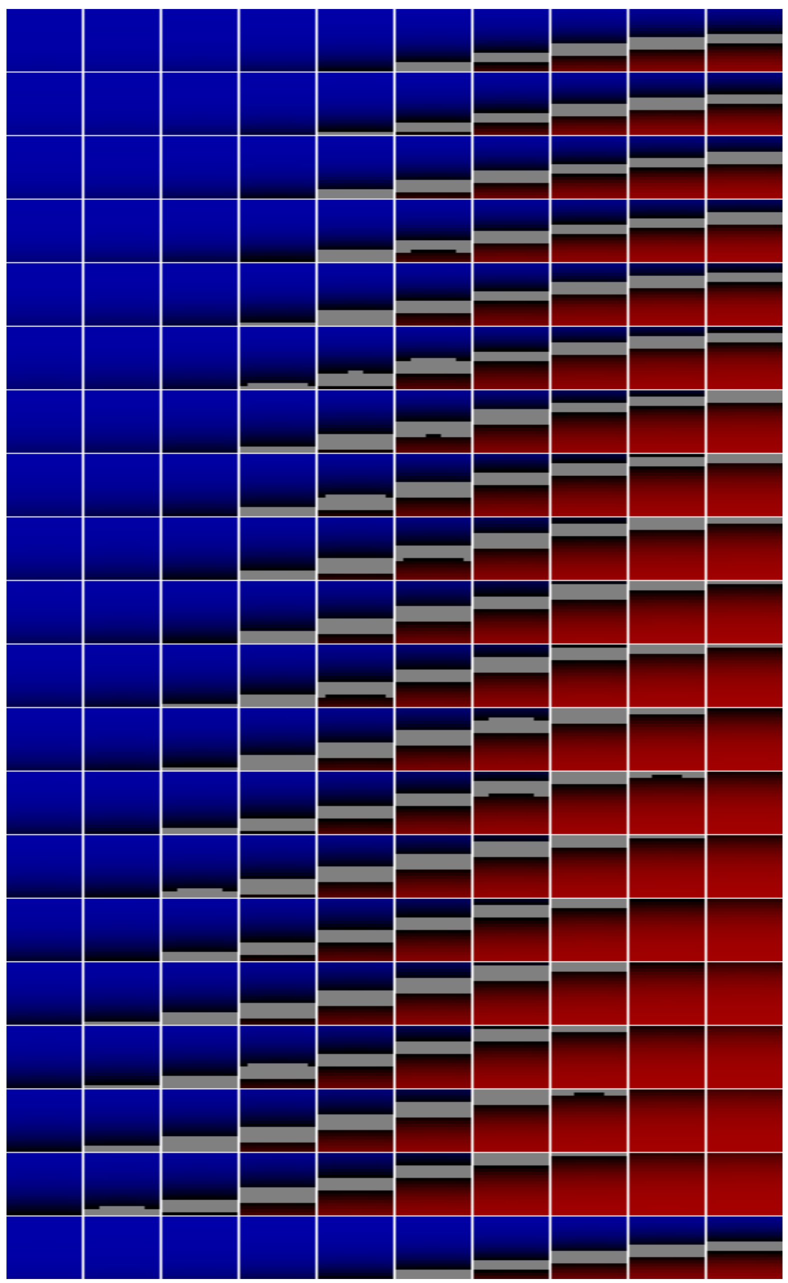
NSGA-II

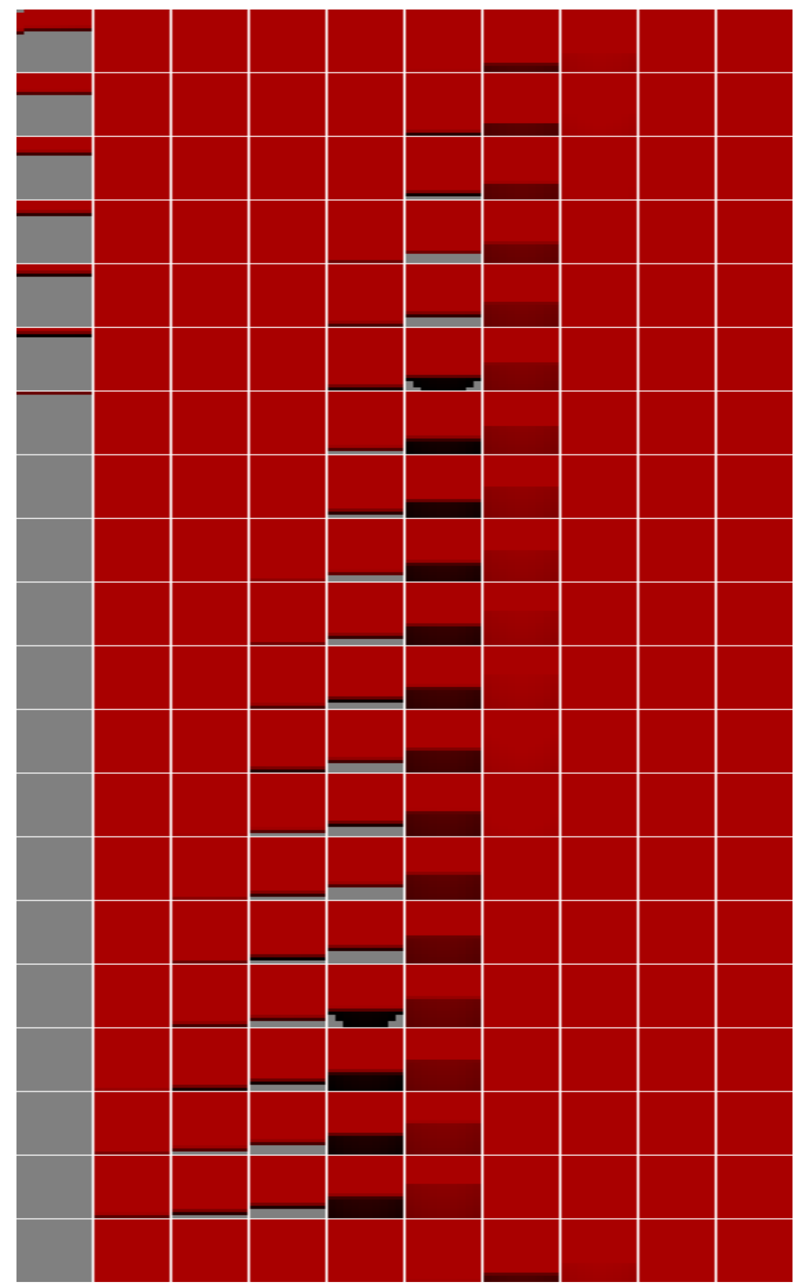
- Pareto-based multiobjective EA optimization
- Parent population, μ, evaluated in domain
- Child population, λ, evolved from μ and evaluated
- μ + λ sorted into non-dominated Pareto fronts
  - **Pareto front:** All individual such that
  - $v = (v_1, \ldots, v_n)$ dominates vector $u = (u_1, \ldots, u_n)$ iff

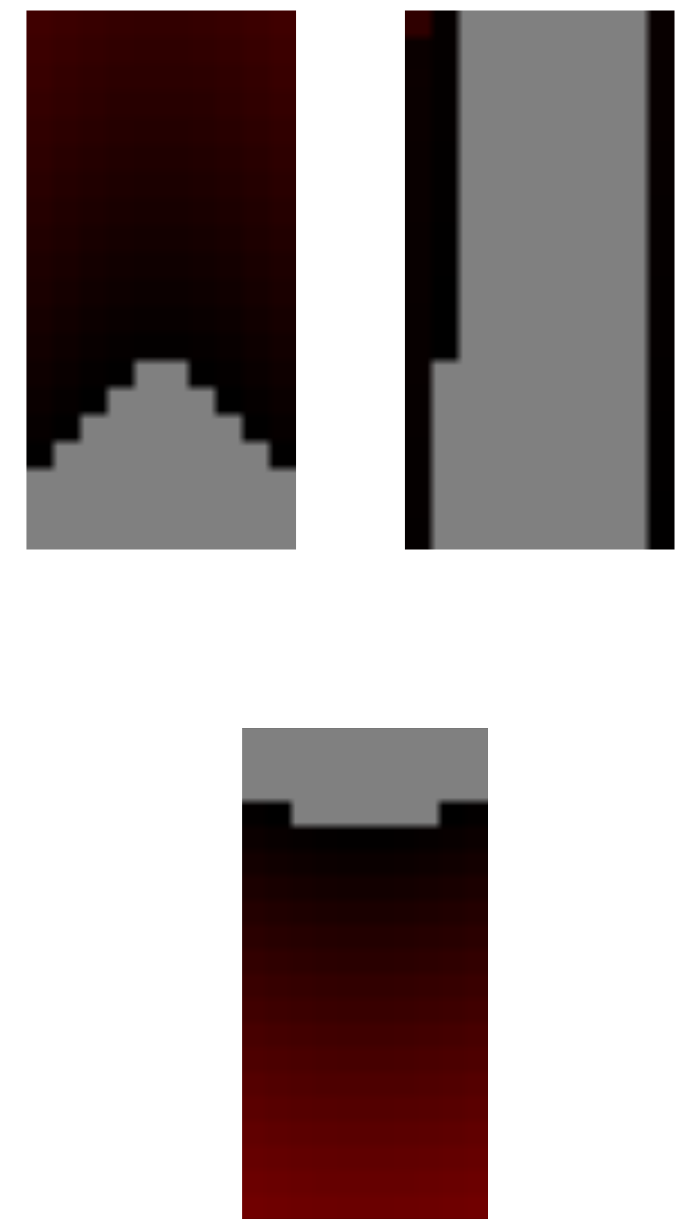
  1. $\forall i \in \{1, \ldots, n\}: v_i \geq u_i$, and
  2. $\exists i \in \{1, \ldots, n\}: v_i > u_i$.
- New μ picked from highest fronts
- Tetris objectives: Game score, time



Visualizing Link Weights







Afterstate Evaluation

- Evolved agents used as afterstate evaluators
- Determine next move from state after placing piece
- All possible piece locations determined, evaluated
- Placement with best evaluation from state chosen
- If placements lead to loss, not considered
- Agent moves piece to best placement, repeats