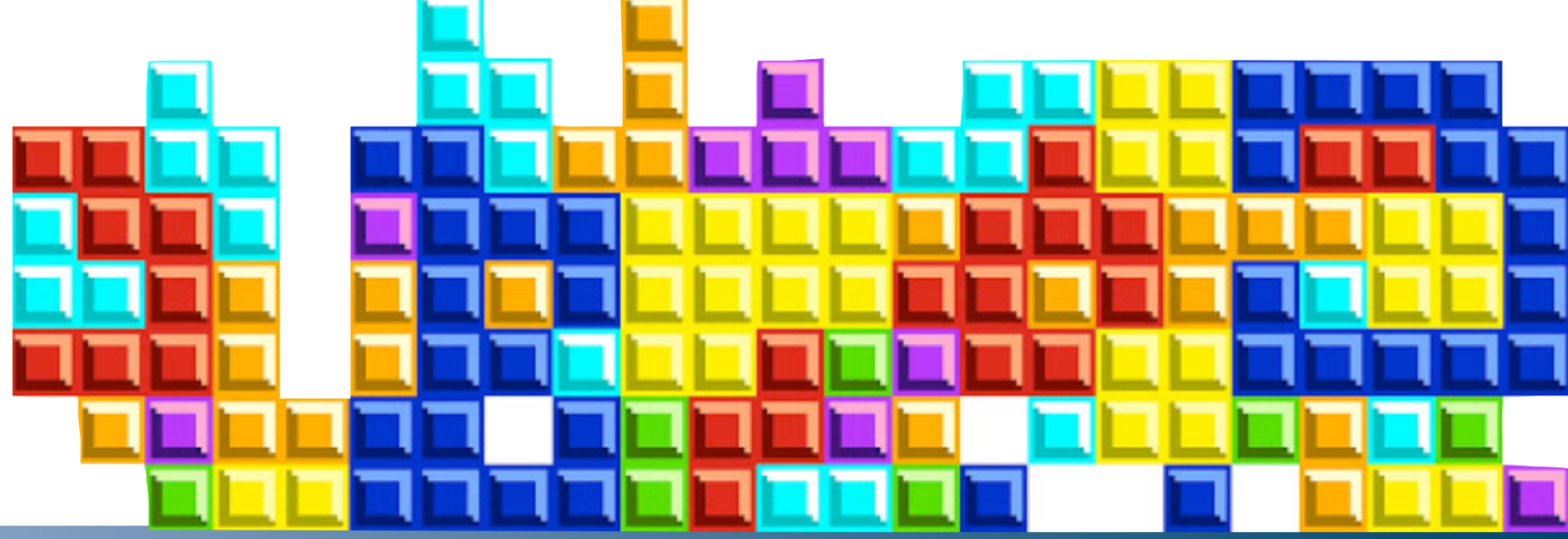

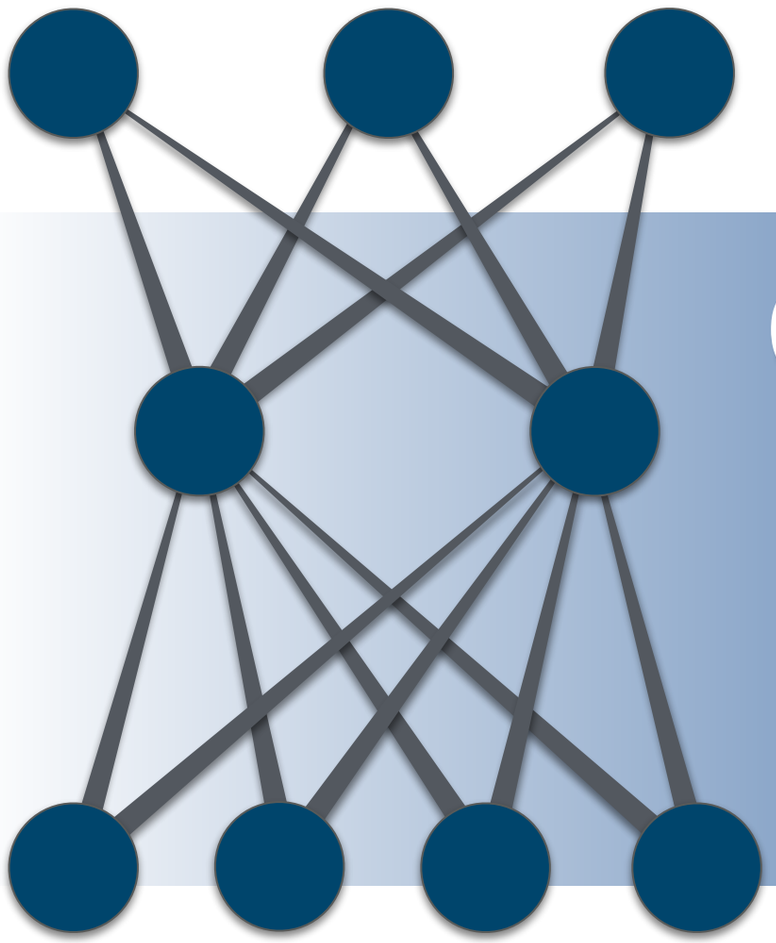

Comparing Direct and Indirect Encodings Using Both Raw and Hand-Designed Features in Tetris

By Lauren Gillespie, Gabby Gonzales and Jacob Schrum

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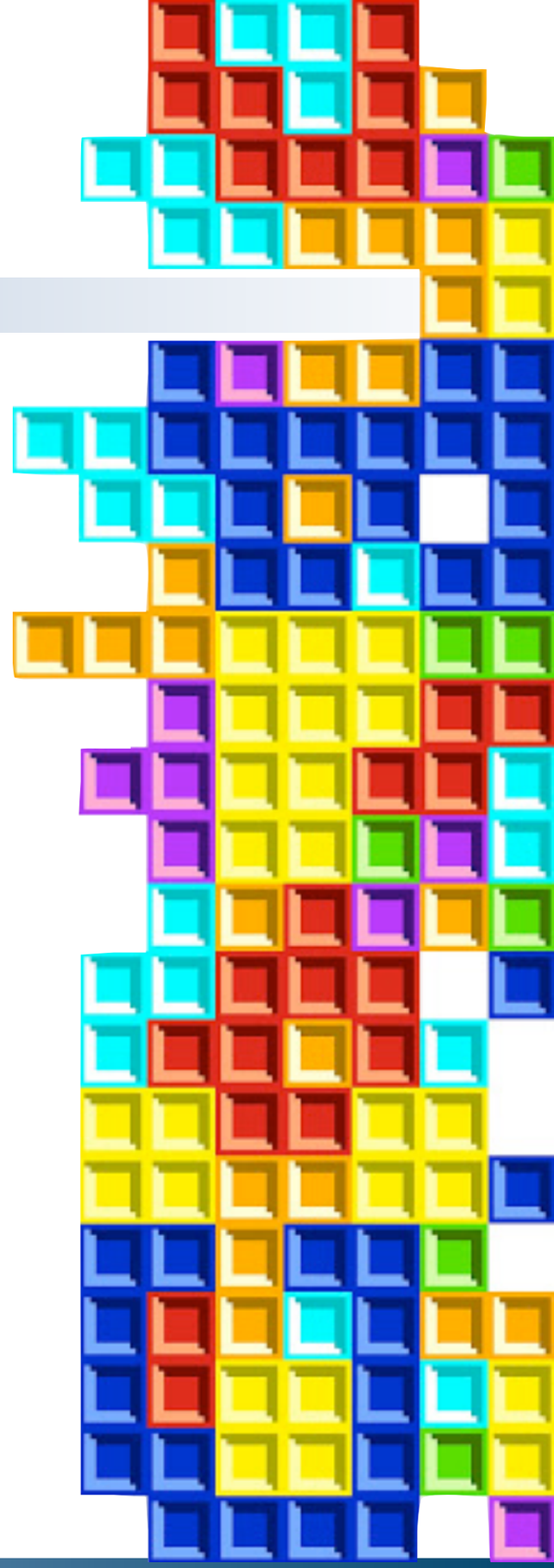
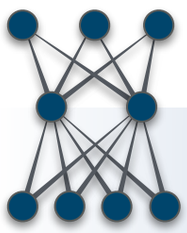
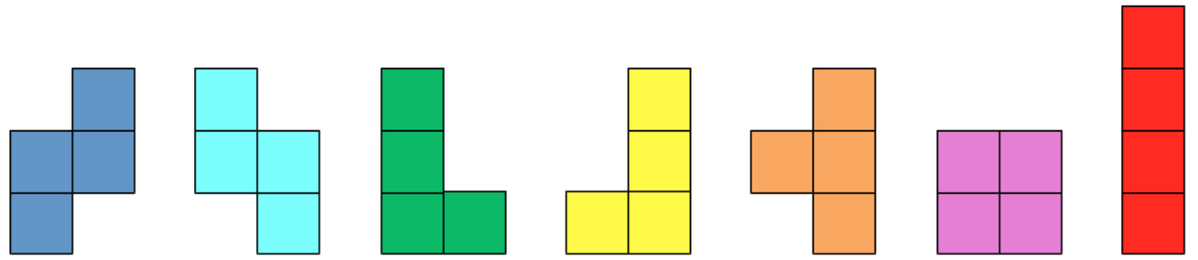
Introduction



- Challenge: Use less domain-specific knowledge
  - ✦ Important for general game-playing agents
  - ✦ Requires using raw features
  - ✦ Difficult to train agents
- This Research
  - ✦ Compare evolutionary algorithm HyperNEAT to NEAT
  - ✦ See if indirect encoding of HyperNEAT advantageous
  - ✦ Also compare with hand-designed features



Tetris Domain



- Consists of 10 x 20 game board
- Orient tetrominoes to clear lines
- Clearing multiple lines = more points
- Hole: open spaces with at least one block above
- Previous Work
  - All use hand-designed features
  - Reinforcement learning† and evolutionary computation‡

†Bertsekas et al. 1996. Temporal Differences-Based Policy Iteration and Applications in Neuro-Dynamic Programming.
‡ Boumaza 2009. On the Evolution of Artificial Tetris Players.

Hand-Designed vs. Raw Features

Hand-Designed

- Hand-picked information of game state as input
- User processes input

Pros:
- ✦ Smaller input space, easier to learn

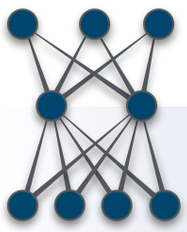
Cons:
- ✦ Very domain-specific, not versatile
- ✦ Human expertise needed

Raw

- One feature per game state element
- Little input processing

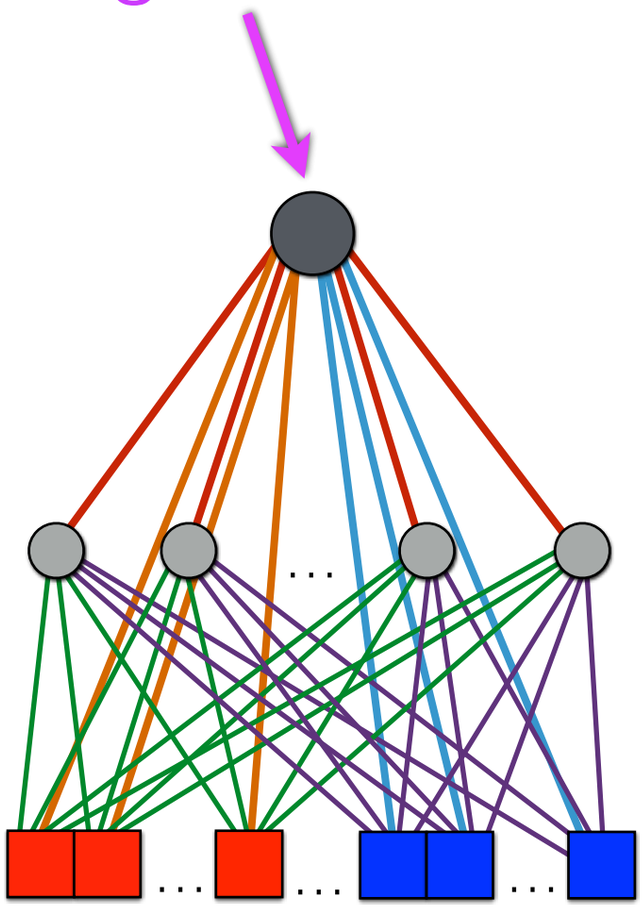
Pros:
- ✦ Less limited by domain†
- ✦ Less human expertise needed

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



NEAT vs. HyperNEAT

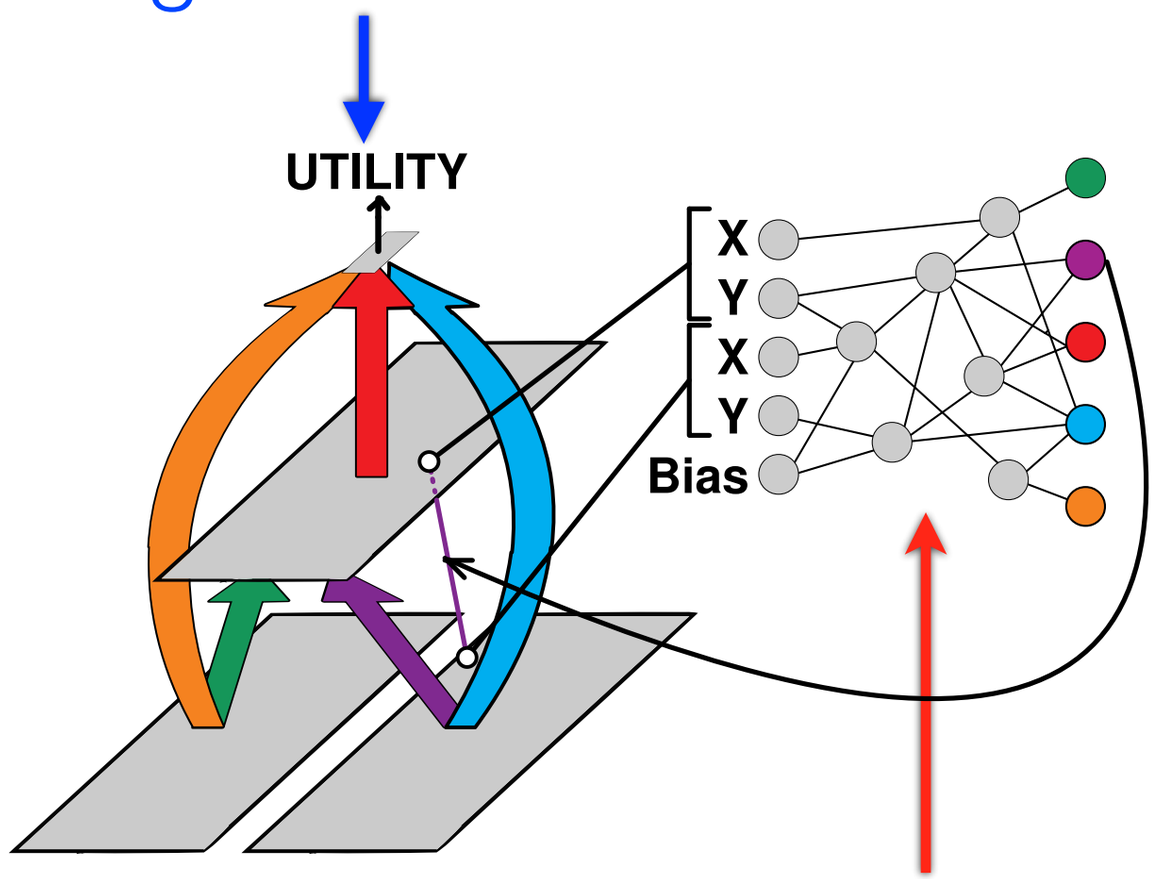
Evolved network
and agent network



NEAT

Direct Encoding

Agent network



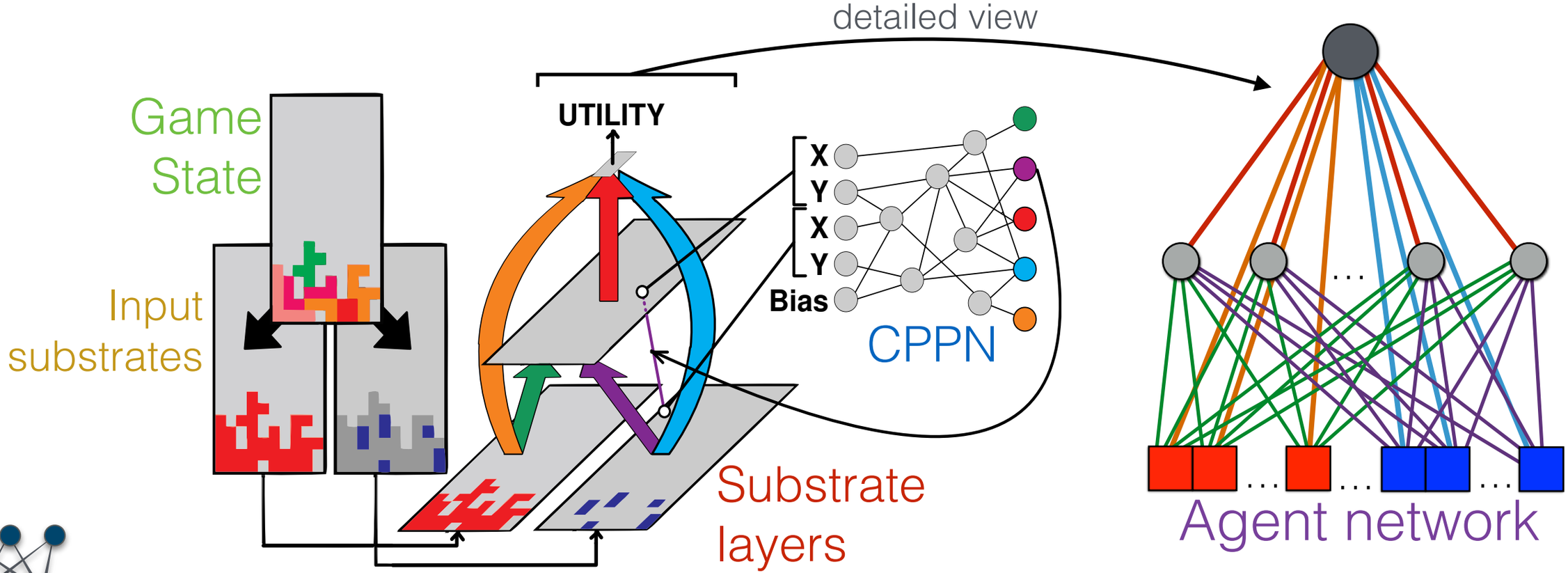
Evolved network (CPPN)

HyperNEAT

Indirect Encoding

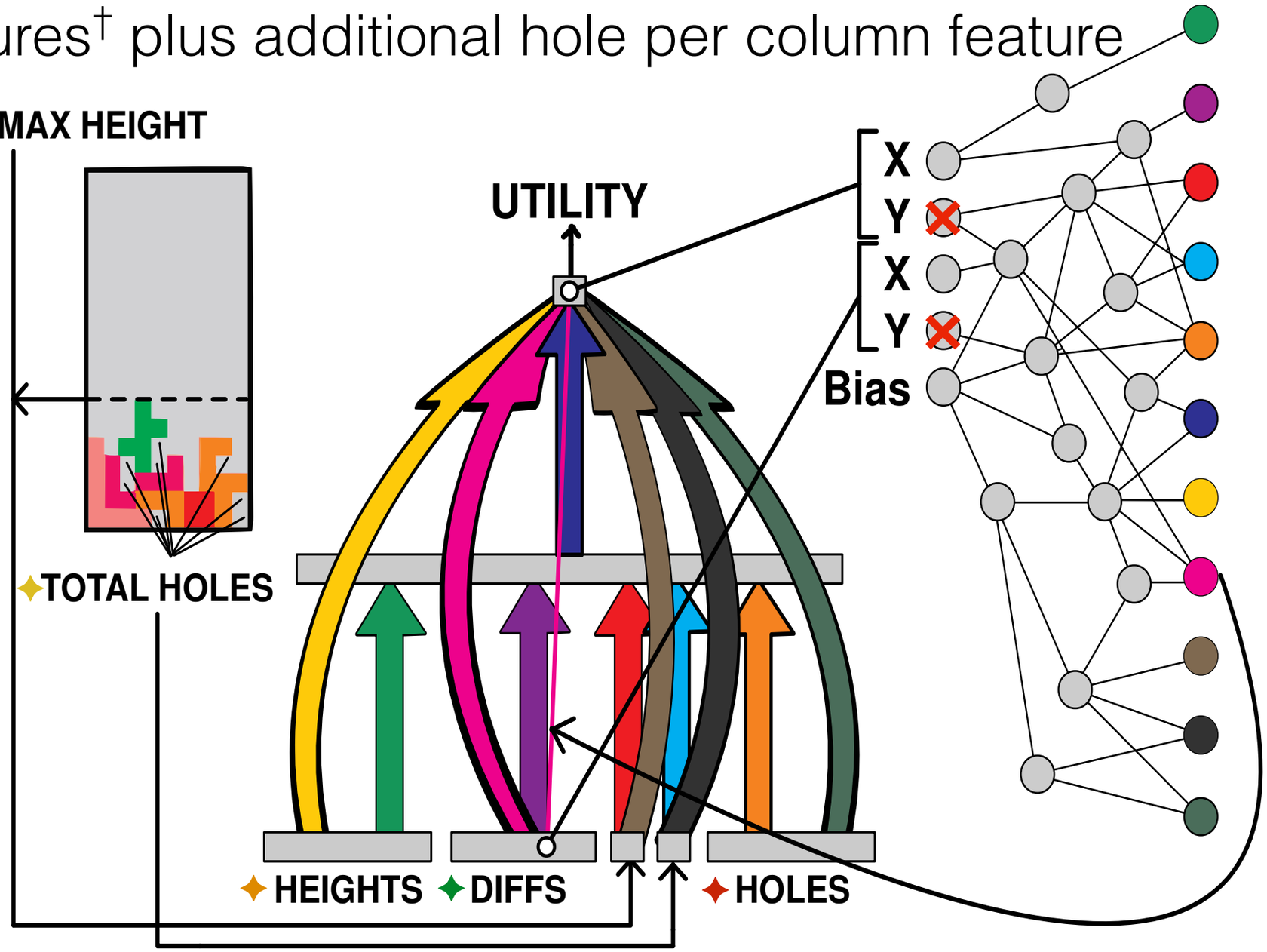
Raw Features Setup

- Board configuration:
  - 2 input sets: location of all blocks, location of all holes
- NEAT: Inputs sets given as linear sequence
- HyperNEAT: Two 2D input substrates



Hand-Designed Features Setup

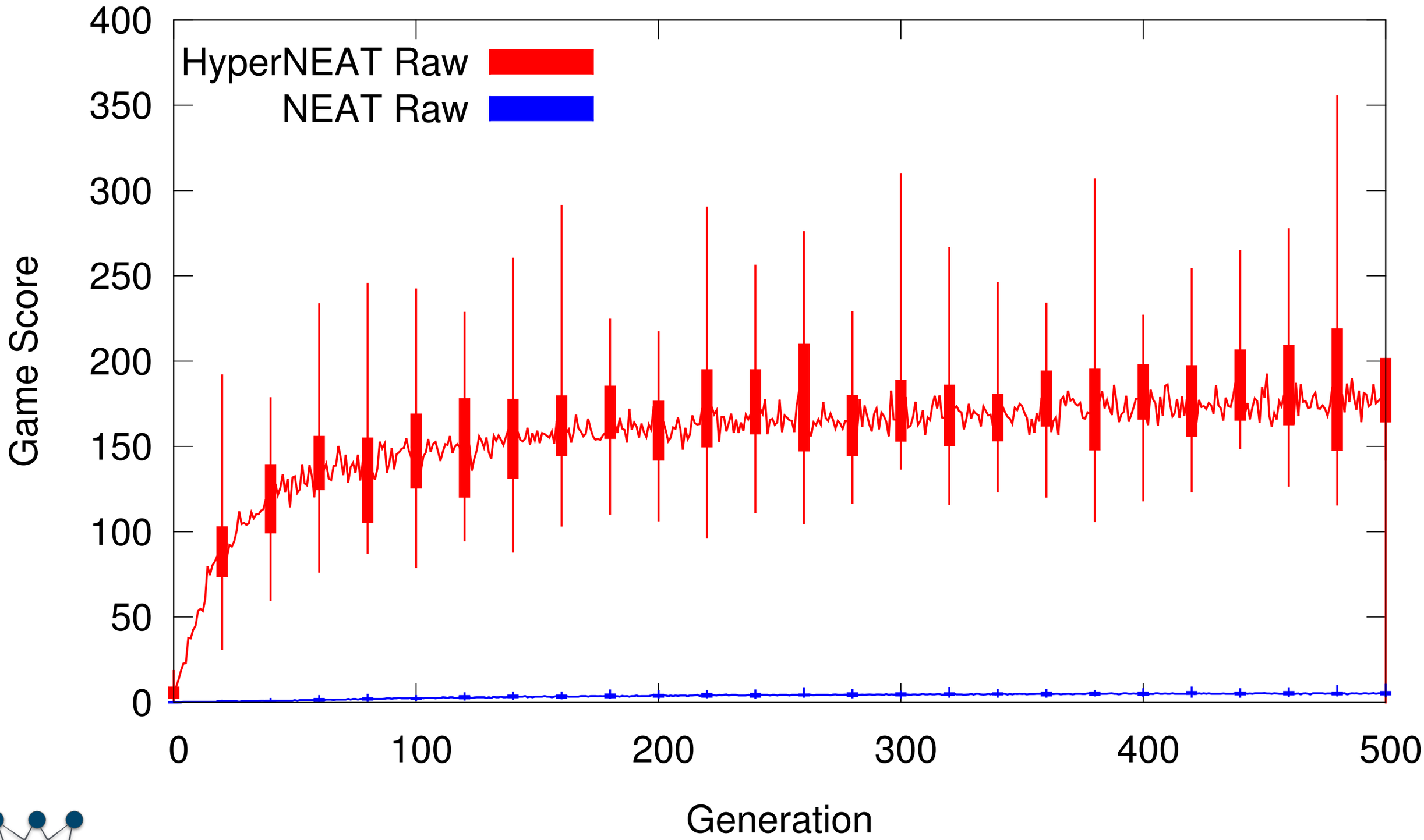
- Bertsekas et al. features† plus additional hole per column feature
- All scaled to [0,1]
- ✦ Column height
- ✦ Height difference
- ✦ Tallest column
- ✦ Number of holes
- ✦ Holes per column



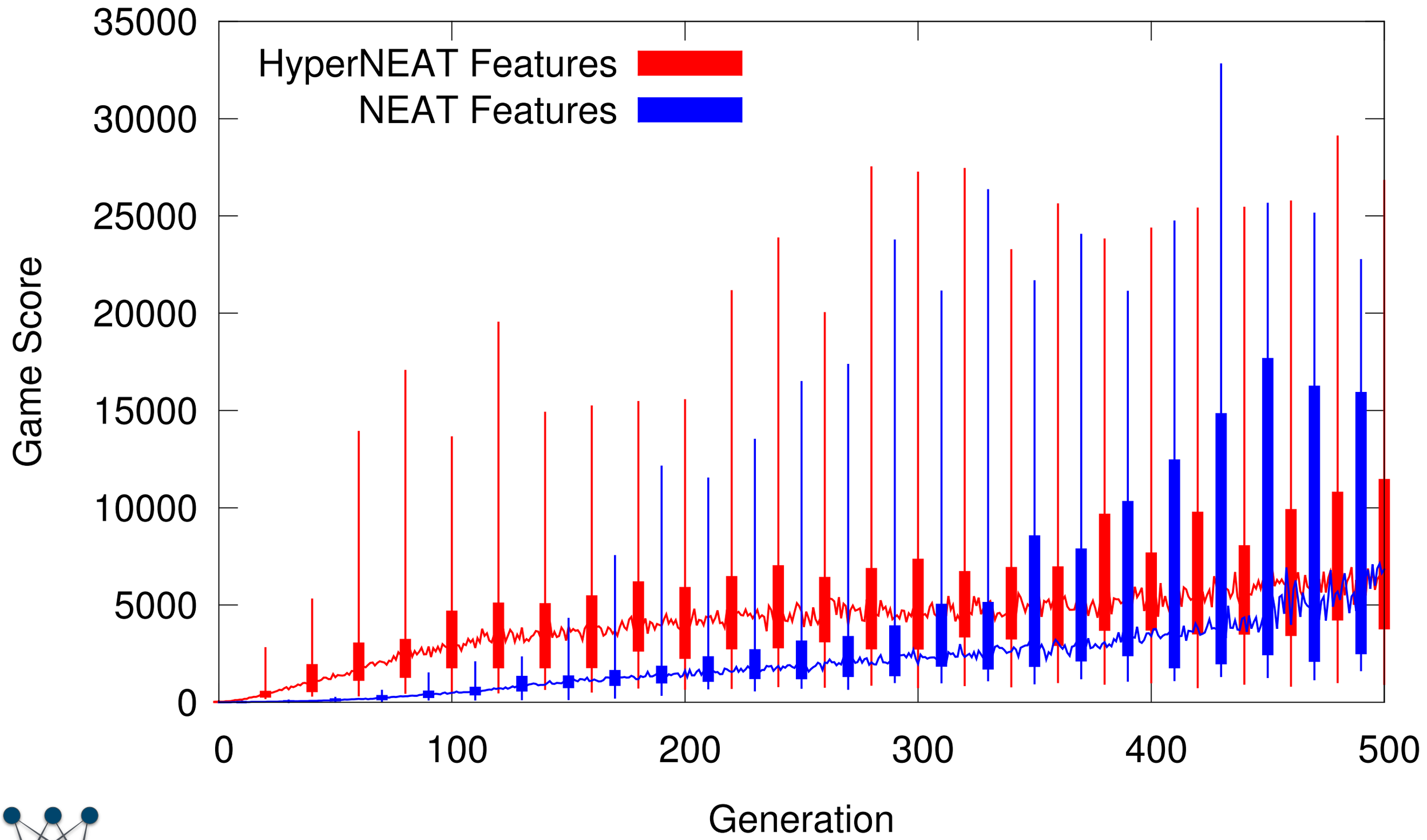
HyperNEAT Setup

† Bersekas et al. 1996. Neuro-Dynamic Programming

NEAT vs. HyperNEAT: Raw Features

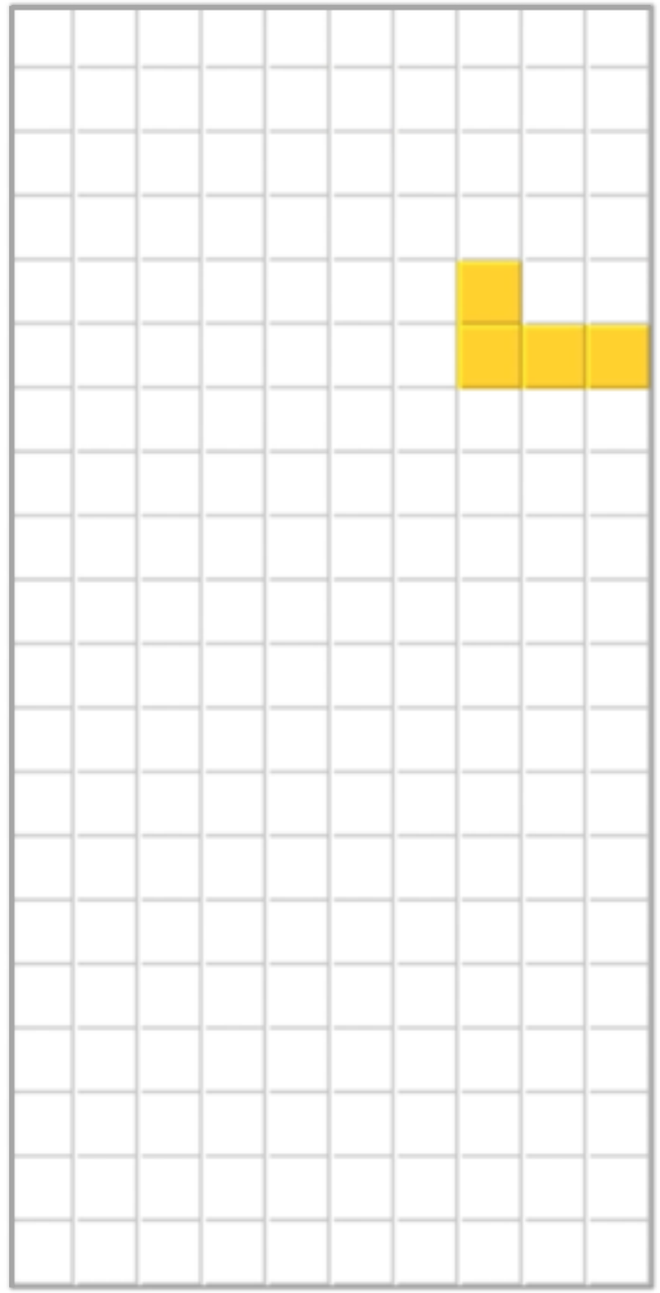


NEAT vs. HyperNEAT: Hand-Designed Features



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

Conclusion

- Raw features
  - Indirect encoding of HyperNEAT effective
  - Geometric awareness an advantage
- Hand-designed features
  - Ultimately NEAT produced better agents
- Future work:
  - HybrID might combine strengths of both
  - Raw Features in other domains, Ms. Pac-Man

Questions?

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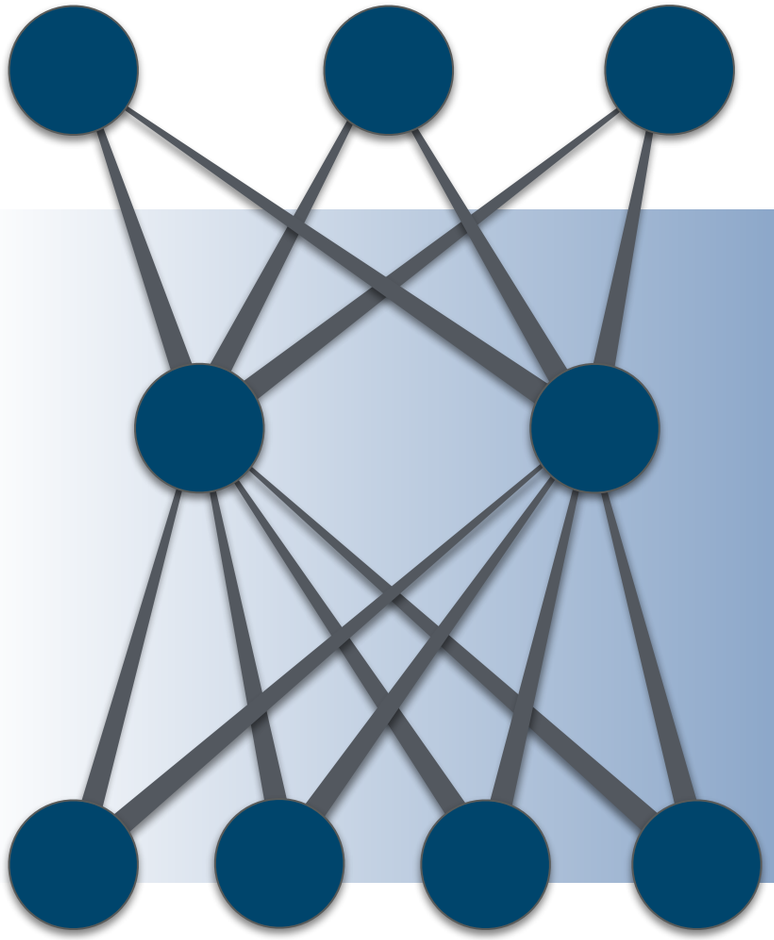
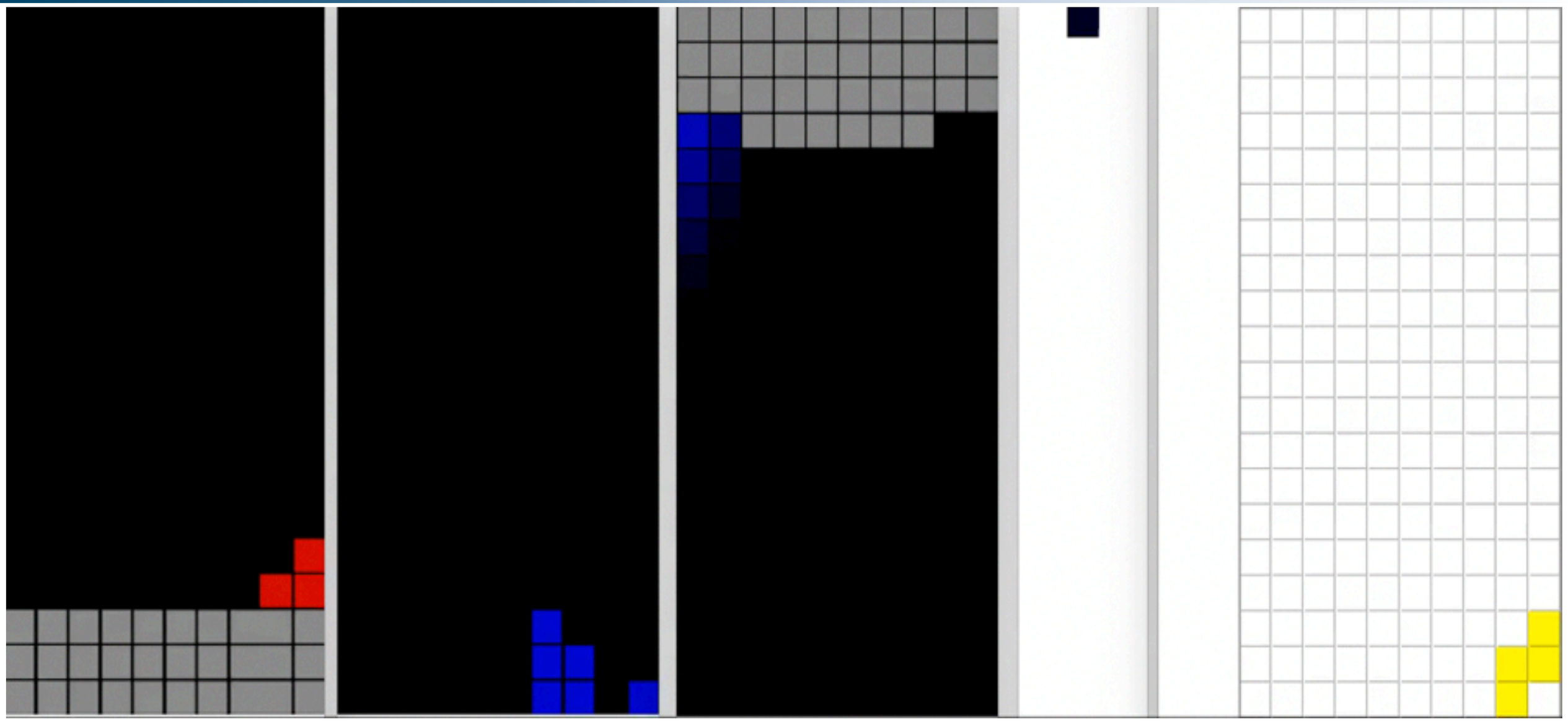
- Movies and Code:

  https://tinyurl.com/tetris-gecco2017



Auxiliary Slides

Visualizing Substrates



Inputs Hidden Output Result

Experimental Setup

- Agent networks evaluated each piece placement
- 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

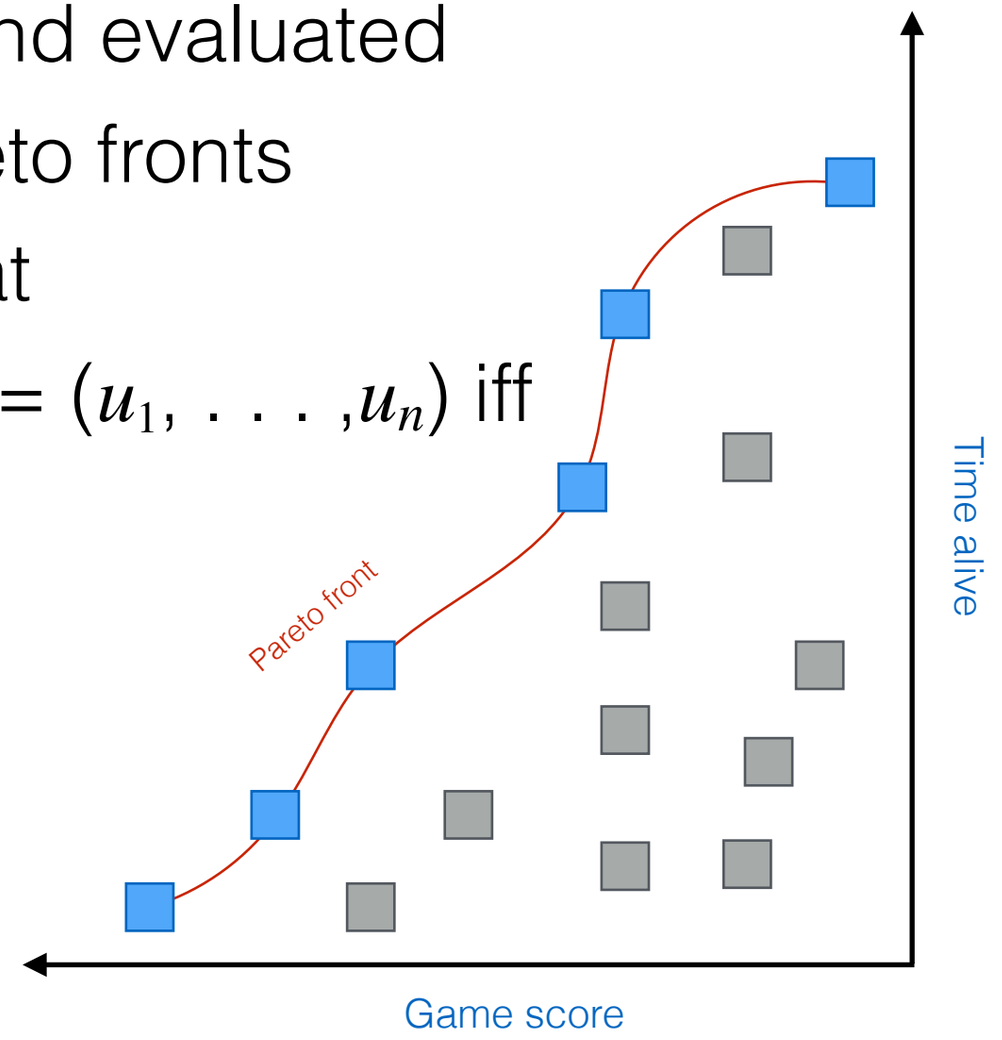
NSGA-II

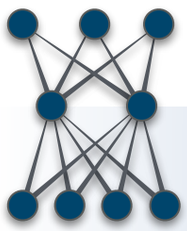
- Pareto-based multiobjective EA optimization
- Parent population, μ, evaluated in domain
- Child population, λ, evolved from μ and evaluated
- μ + λ sorted into non-dominated Pareto fronts
  - **Pareto front:** All individual such that
  - $v = (v_1, \ldots, v_n)$ dominates vector $u = (u_1, \ldots,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

1. $\forall i \in \{1, \ldots, n\}: v_i \geq u_i$, and

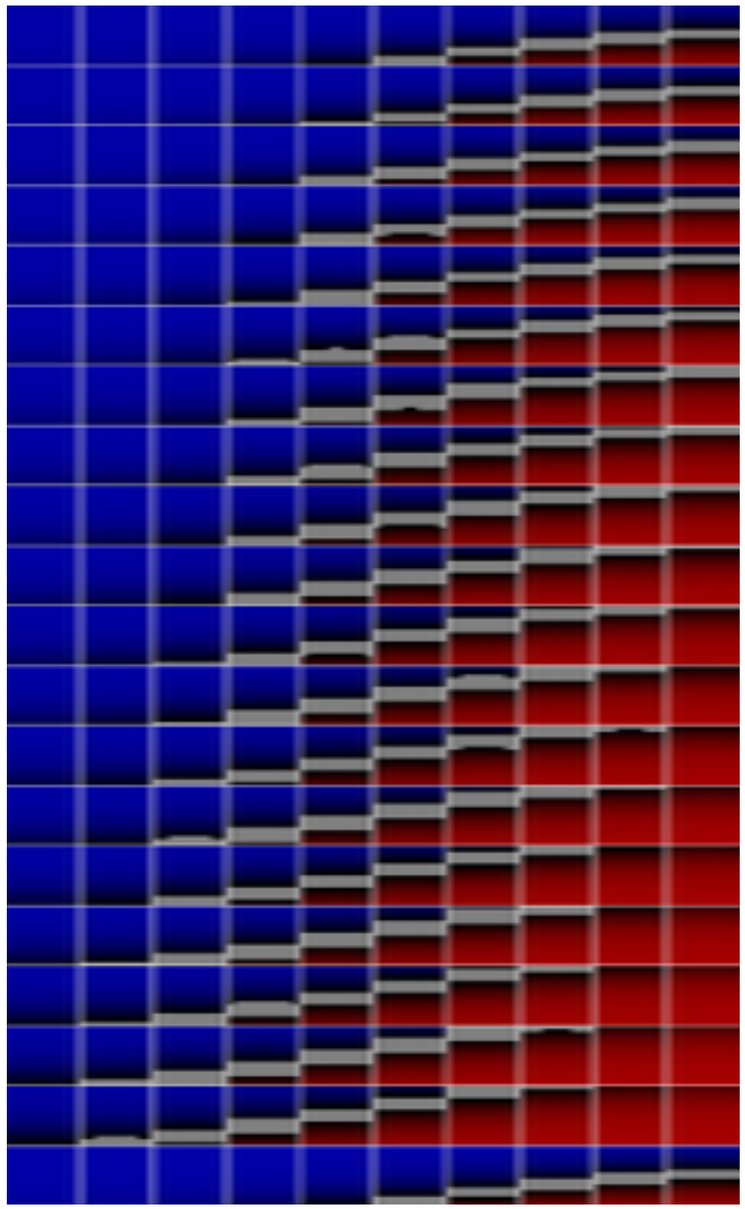
2. $\exists i \in \{1, \ldots, n\}: v_i > u_i$.

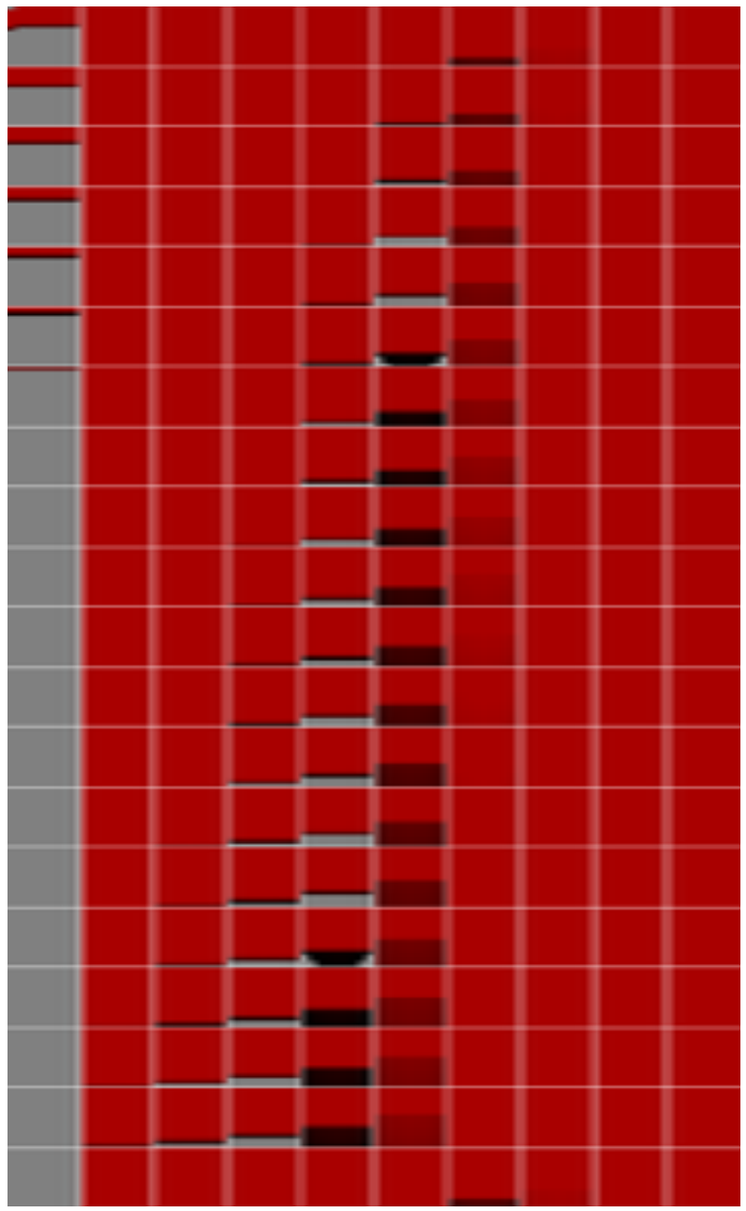
- New μ picked from highest fronts
- Tetris objectives: Game score, time

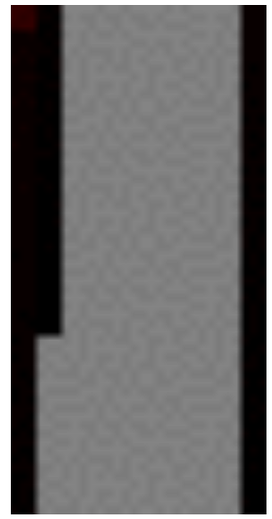




Visualizing Link Weights

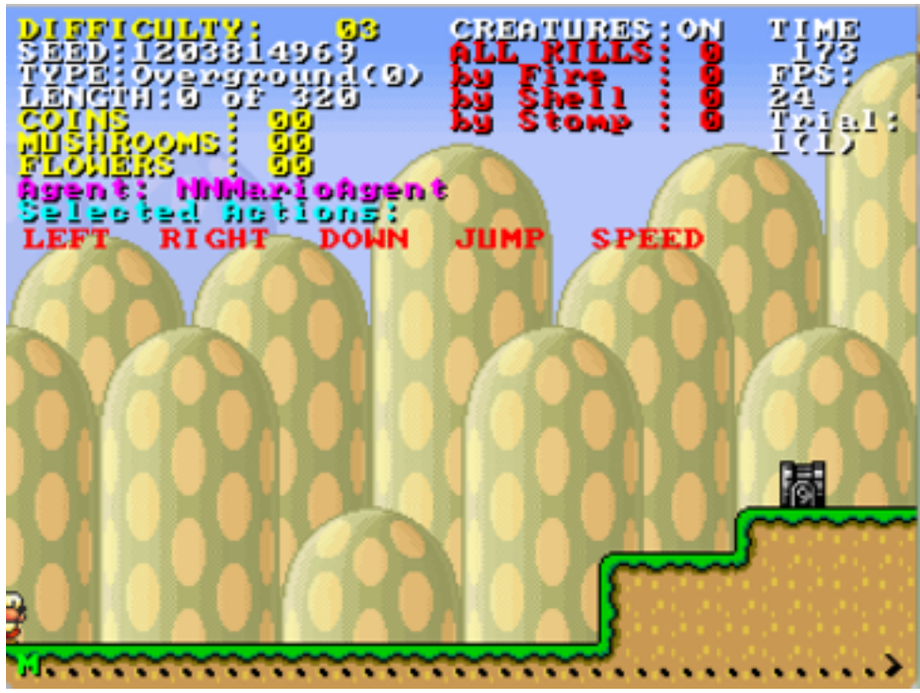






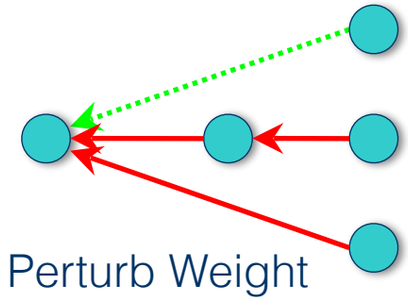
Future Work

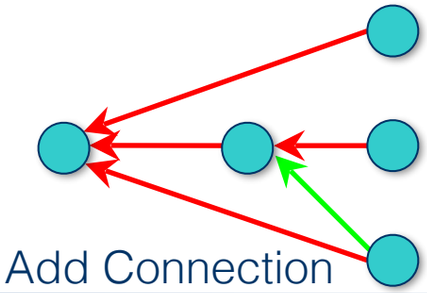
- HybrID†
  - ✦ Start with HyperNEAT, switch to NEAT
  - ✦ Gain advantage of both encodings
- Raw feature Tetris with Deep Learning
- Raw features in other visual domains
  - ✦ Video games: DOOM, Mario, Ms. Pac-Man
  - ✦ Board games: Othello, Checkers

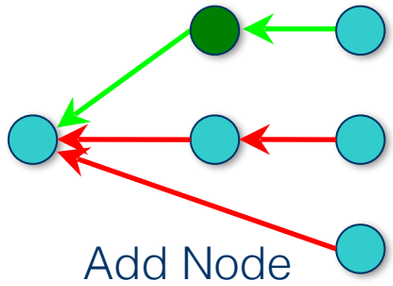


† Clune et al. 2004. HybrID: A Hybridization of Indirect and Direct Encodings for Evolutionary Computation.

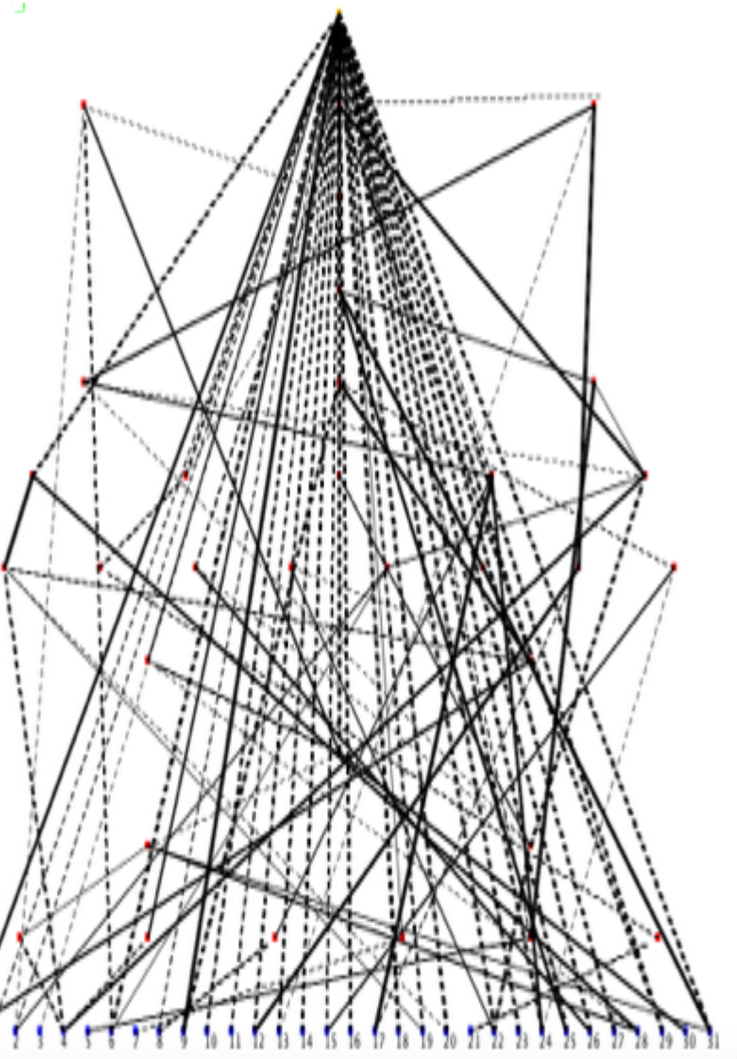
NEAT





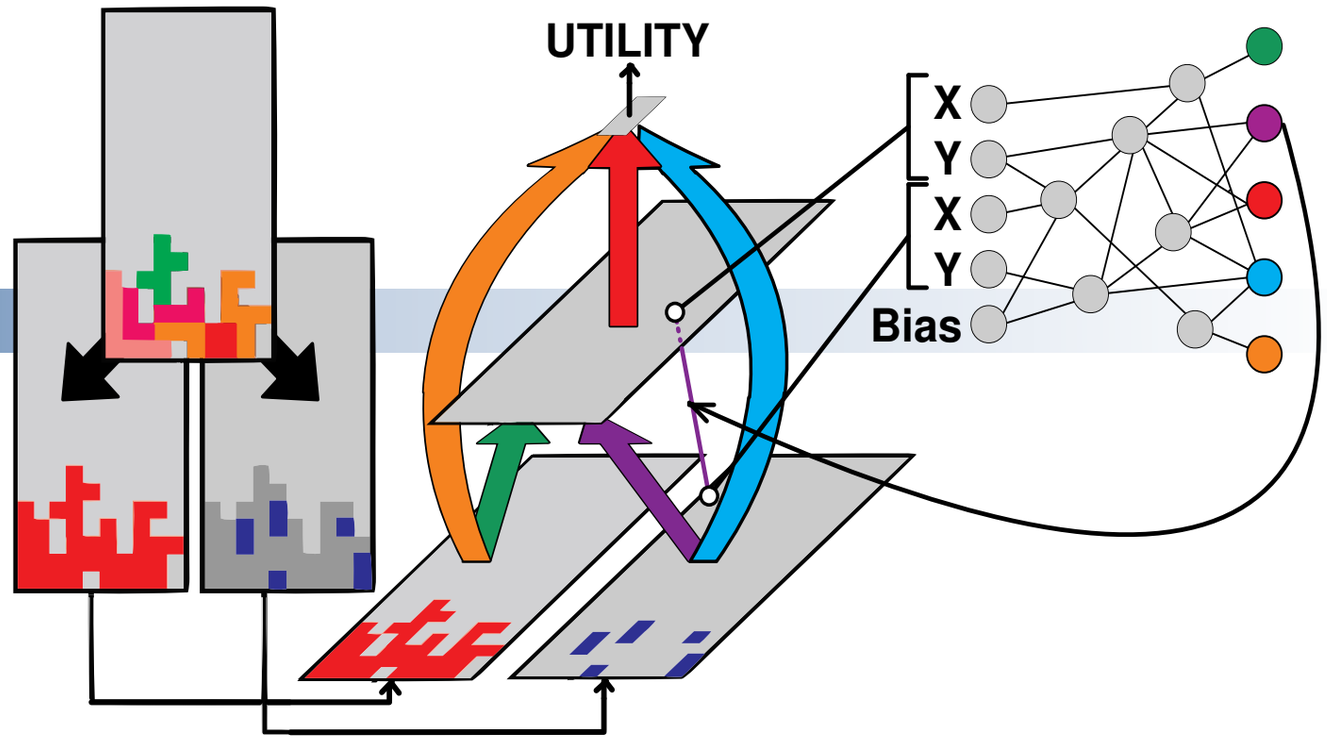


- NeuroEvolution of Augmenting Topologies†
- Synaptic and structural mutations
- Direct encoding
  - ✦ Network size proportional to genome size
- Crossover alignment via historical markings
- Inefficient with large input sets
  - ✦ Mutations do not alter behavior effectively



† 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

Evolutionary Algorithms (EA)

NEAT

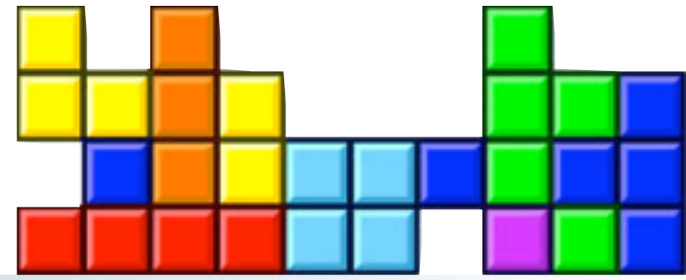
- NeuroEvolution of Augmenting Topologies†
- Mutates structure and weights
- Direct encoding
  - ✦ Network size = genome size
- Inefficient with large input sets
  - ✦ Mutations not as effective

HyperNEAT

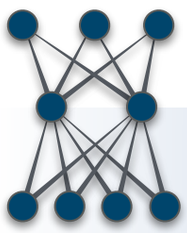
- Hypercube-based NEAT†
- Indirect encoding
  - ✦ Evolved CPPN *indirectly* plays game through agent network
- Geometric awareness
  - ✦ Agents can learn from domain geometry
- Better with large input sets
  - ✦ Geometric awareness gives agents more information

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

Afterstate Evaluation

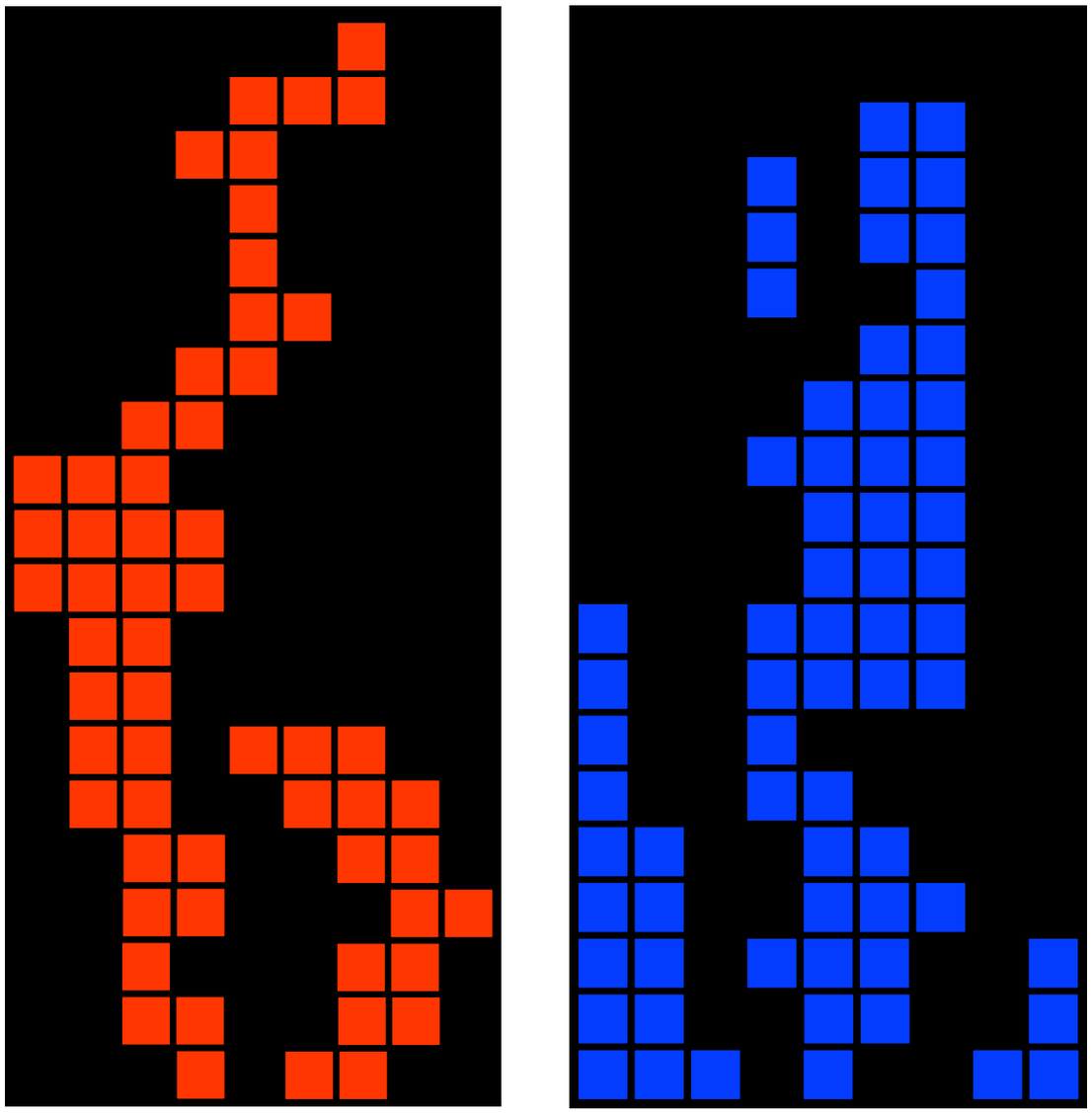


- Evolved agents used as afterstate evaluators
- Determine next move from state after placing piece
- All possible piece locations determined, evaluated
- Placement with best evaluation from state chosen
- If placements lead to loss, not considered
- Agent moves piece to best placement, repeats



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