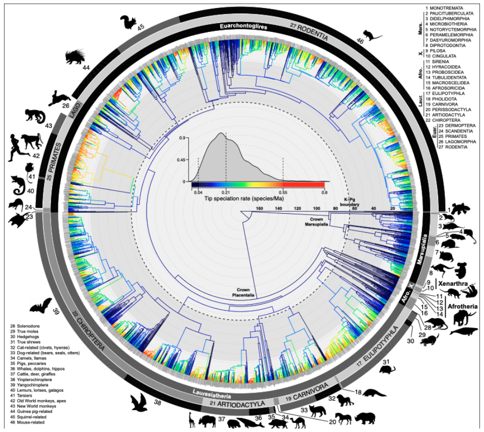
Multiobjective Optimization in Evolution

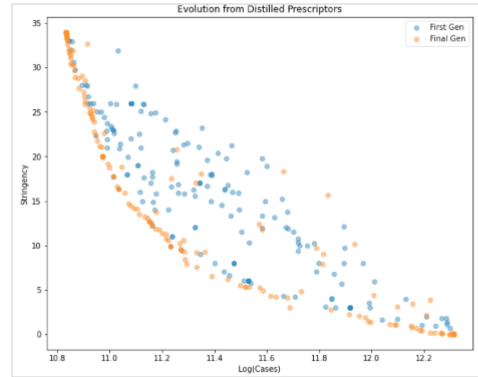
- Multiobjectivity is a natural extension of quality-diversity methods.
- Inspired by biology: organisms must balance multiple conflicting objectives.
- Solutions can be successful in many ways, promoting diversity in the population.



Mammals

Pareto Front in Multiobjectivity

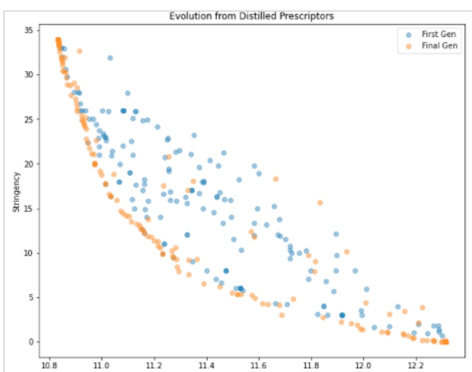
- Multiobjective optimization results in a Pareto front of solutions.
- No single solution is better across all objectives.
- Trade-offs allow multiple niches of high-performing solutions.
- Solutions on the Pareto front can be chosen based on deployment conditions or other criteria.



Cases vs. stringengy in NPIs

Multiobjective Evolution Methods

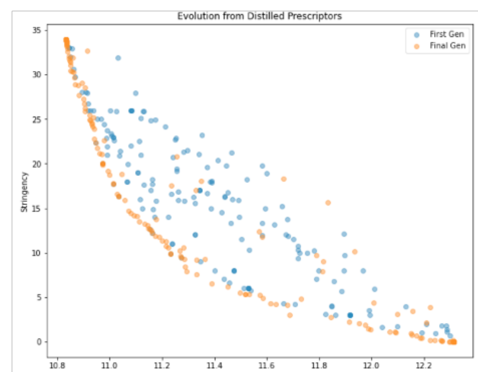
- Pareto front can be formed from the population of standard evolution.
  - E.g. combine objectives as a weighted average.
  - May not get a comprehensive front though.
- Multiobjective optimization method like NSGA-II can be used to evolve the Pareto front explicitly
  - Evaluate candidates in successive layers of nondominance.
  - Broad coverage as a front.



Cases vs. stringengy in NPIs

Boosting Diversity through Multiobjectivity

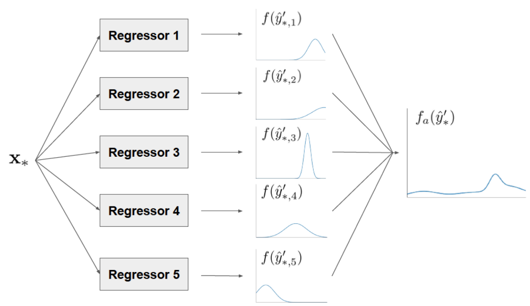
- Multiobjective evolution naturally encourages diversity.
  - Multiple objectives create different success paths, forming niches.
- To further increase diversity:
  - Novelty can be used as a secondary objective.
  - NEAT and other speciation methods can further enhance diversity.



Cases vs. stringengy in NPIs

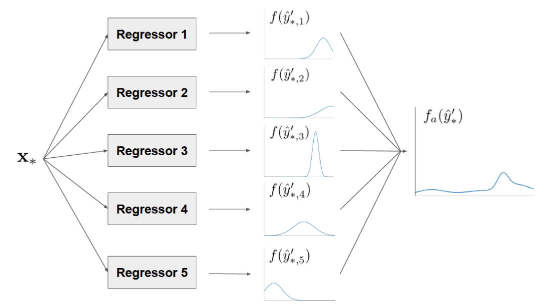
Ensembling Diverse Solutions

- Ensembling can take advantage of this diversity.
- Ensembling involves training multiple models and combining them.
- Each model contributes different insights, improving overall performance.
- Inspired by studies in psychology, business, and social science, which show that diversity improves decision-making in human teams



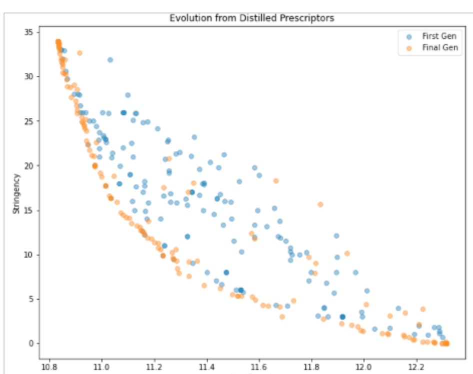
Basic Ensembling Techniques

- Simple combinations: Voting, weighted averaging.
  - All experts activated and their output combined.
- Mixtures of Experts
  - Different experts used for different input regions.
- Effective both in classification and regression; prediction and prescription.



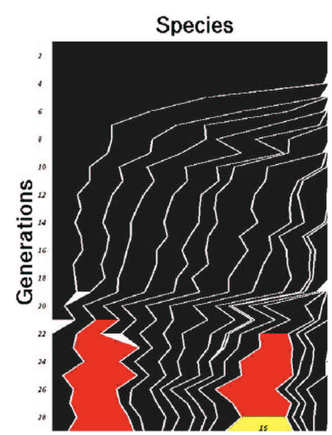
Ensembling in Evolutionary Computation

- Evolutionary Algorithms (EAs) naturally create diverse populations.
- Final population members often have different skills, forming a good ensemble.
- Multiobjective optimization enhances diversity for ensembling.



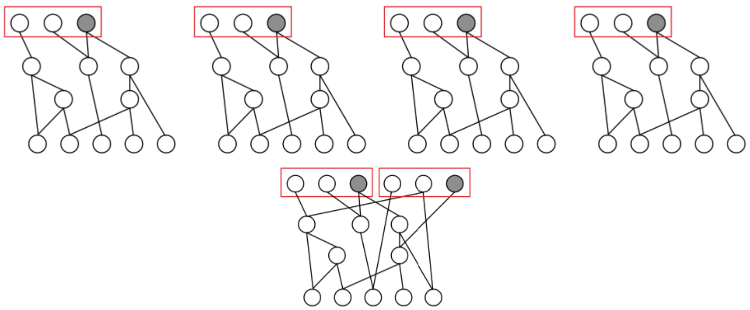
NEAT and Speciation in Ensembling

- NEAT employs a speciation mechanism to encourage diversity.
- Species champions can be used as ensemble members.
- Combine with voting, averaging, or winner-take-all for improved performance.



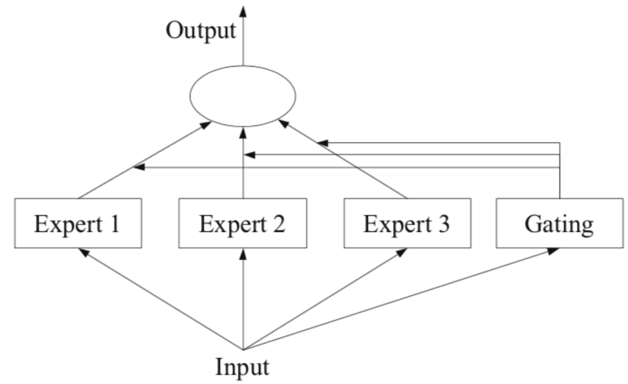
Ensembling Through Confidence Estimates

- Each network estimates whether they are the best choice to control the agent at this point.
  - A preference output, separate from the task outputs.
  - Networks bet on having the right answer, maximizing returns.
- Networks act as ensemble members with preference neurons guiding combination.
  - Can be a simple choice, or preference-weighted combination.
  - Can be evolved as separate networks, or modules in one network.



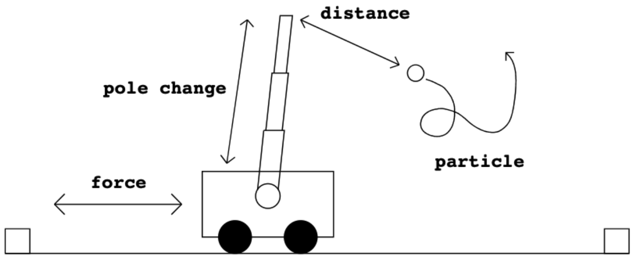
Ensembling Through a Gating Network

- A NEAT population evolved in the control task first.
- Then a gating network evolved to select which controller to use when, choosing among the species.



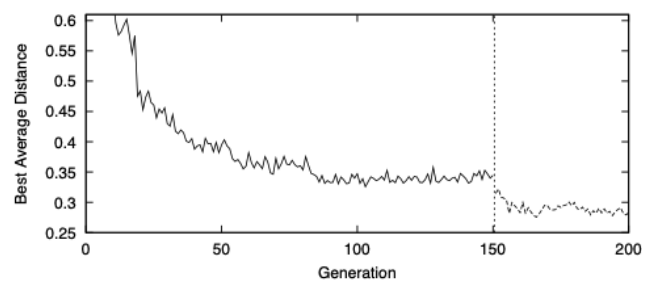
Ensembling Through a Gating Network

- Tested in the fly-swatting task:
  - An extension of the cart-pole task with more diverse state space.
  - Pushing left and right; extending and contracting the pole.
  - Aim to keep the pole tip on the target.



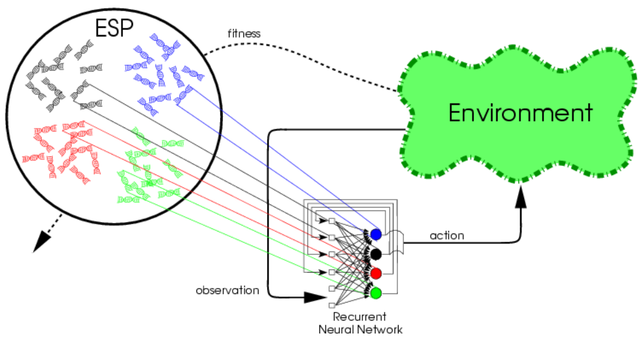
Gated Ensembling Example

- The gating network partitions the space and uses different NEAT networks at different times.
- Best results with ensemble size of eight.
- Gated ensembling significantly boosts performance.



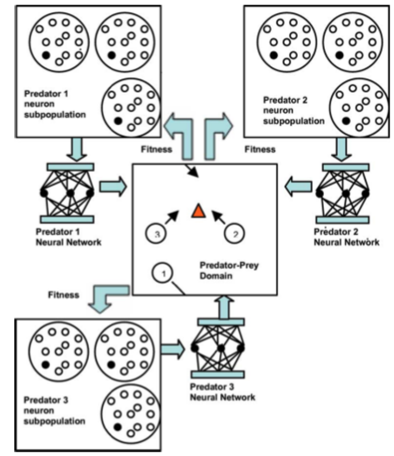
Ensembling in Enforced Sub-Populations

- Enforced SubPopulation (ESP) method evolves each neuron of the network in a separate subpopulation.
  - Each neuron encodes its own weights.
  - A network is formed by selecting randomly from subpopulations.
  - The neurons inherit the fitness of the network; they evolve to cooperate.
- Good network require different neurons; diversity is thus encouraged.



Hierarchical ESP

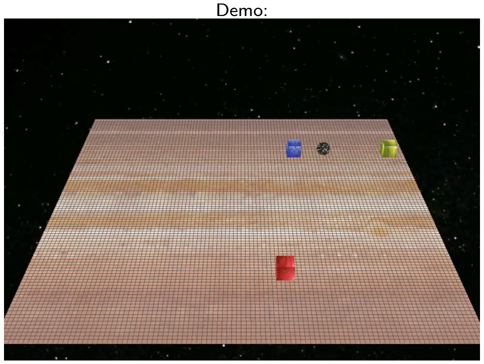
- Hierarchical ESP extends the approach to teams of networks.
- It forms a principled ensemble:
  - Each neuron and each network is evolved for a specific role.
  - Not just diversity, but optimized diversity.
- Particularly powerful in cooperative multiagent tasks.
  - E.g. a team of predators capturing a prey:



Hierarchical ESP Example

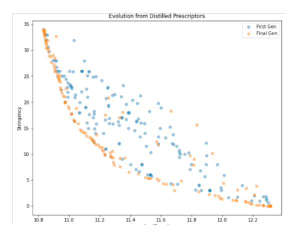
- Particularly powerful in cooperative multiagent tasks.
- E.g. a team of predators capturing a prey:
  - One network chases, another captures the prey.
  - One neuron turns towards the agent; another away from teammate.

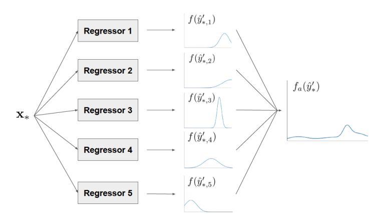
Demo:



Multiobjectivity and Ensembling Conclusions

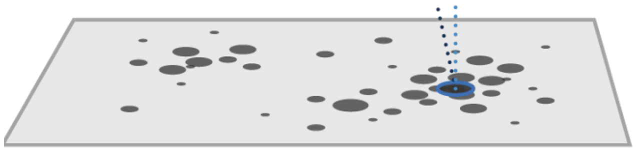
- Multiobjective optimization promotes diversity.
  - Pareto fronts are diverse by definition.
  - Especially by making novelty a secondary objective.
- Ensembling is a powerful way of taking advantange of this diversity.
  - More robust decision-making in complex domains.
  - Can be extended with various techniques to suit specific problems.
- Both are natural extensions of population-based search.





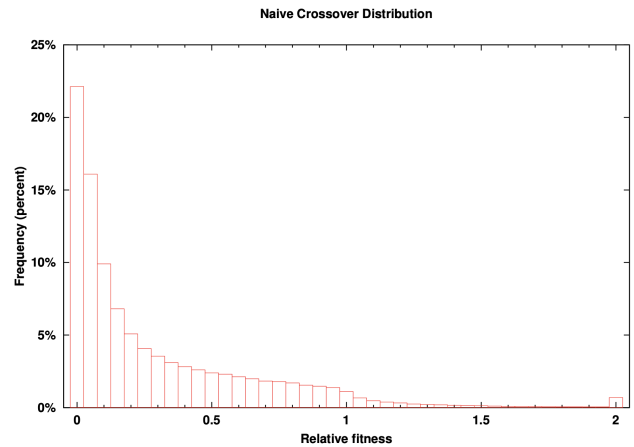
Population Culture in Evolution

- Population culture refers to the knowledge across individuals.
- Includes both common behaviors and unique knowledge.
- Can be used to improve evolution in several ways: multiobjectivity and ensembling; culling, training, selection, pruning...



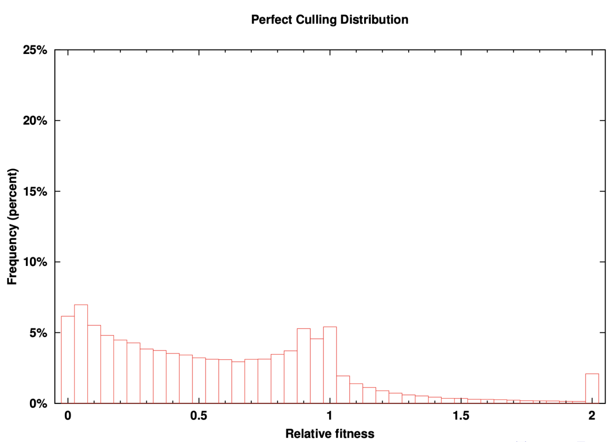
Culling: Speeding up Evolution

- Culling generates a large number of offspring, only keeping the most promising.
- Efficient because "most crossovers are awful".



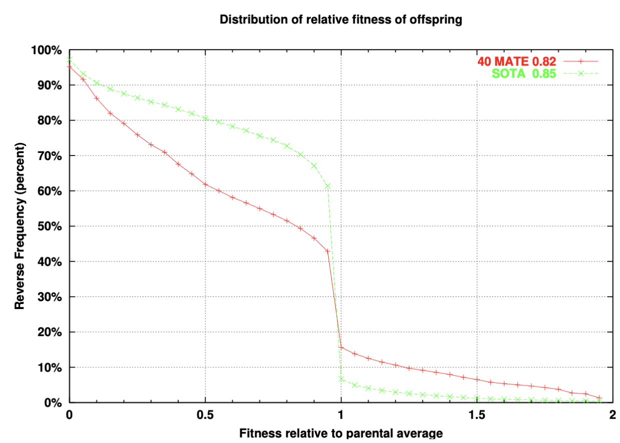
Recognizing Promising Offspring

- Approximate evaluations help recognize good offspring fast.
  - Use a syllabus of inputs and compare answers to prominent population members.
  - Effectively identifies non-viable offspring.
  - Expensive fitness evaluations not necessary.
- Can speed up neuroevolution by a factor of 3 in tasks like pole balancing.
- E.g. culling from a litter of 8:



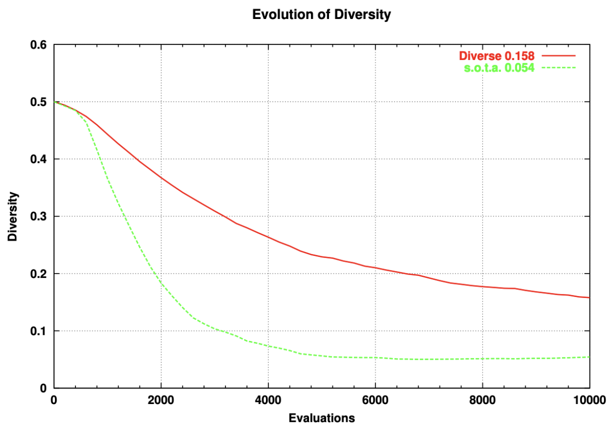
Cultural Selection of Parents

- Parents are chosen based on diversity, not just fitness.
- First parent based on fitness, second chosen as maximally different (in its answers to the syllabus).
- Increases the chance of combining complementary strengths in offspring.
- Improves even though the second parent has low fitness:



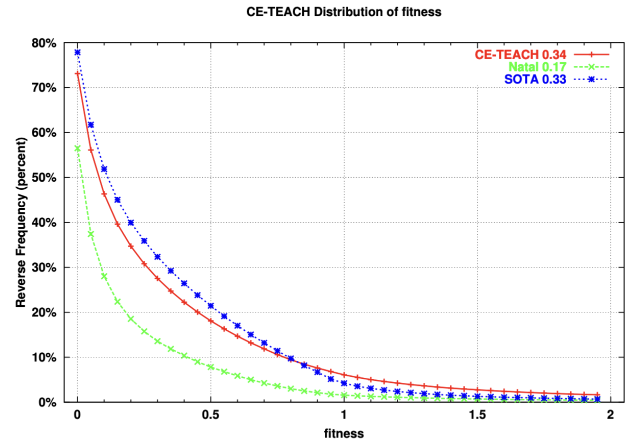
Maintaining Diversity in the Population

- The syllabus can also be used to decide which solutions to discard.
- Find two closest solutions, discard the one with lower fitness.
- Increases diversity and accelerates evolution by 30%.



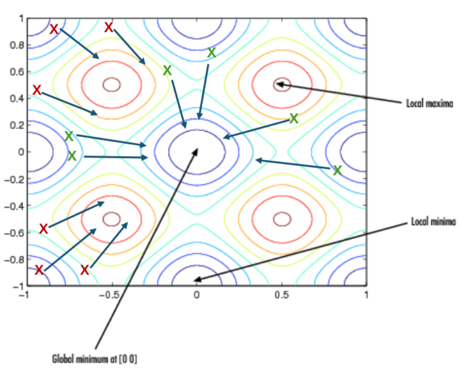
Using Culture to Enhance Learning

- Leverage population champions' behaviors as a training set.
- Select the offspring that performs well after training (i.e. utilize the Baldwin effect, not Lamarckian evolution).
- Speeds up neuroevolution by an order of magnitude.
- But performance at birth is poor! What's going on?



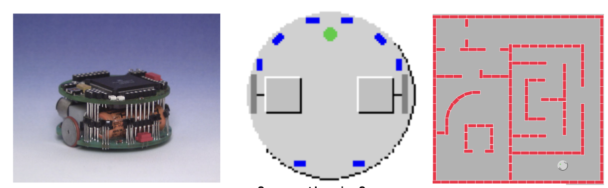
Synergetic Development

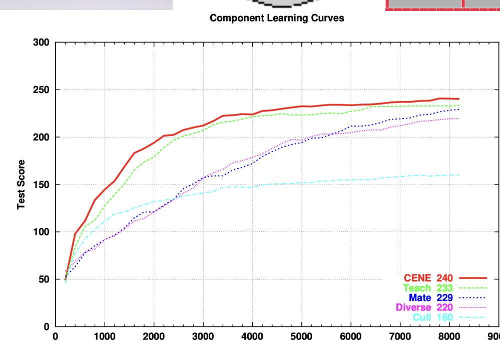
- We've seen this before: Evolution discovers good starting points for learning rather than near-optimal solutions.
  - Learning will happen, so evolution discovers how to take it into account.
  - A synergy between learning and evolution.
- Solutions are more robust and more effective.



Putting it Together

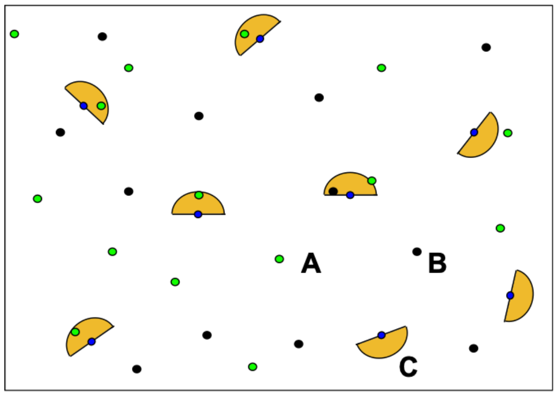
- Culture helps several aspects of evolution.
- Which methods are the most effective depends on the problem; Can be combined for a robust effect.
- E.g. the simulated Khepera maze running task:





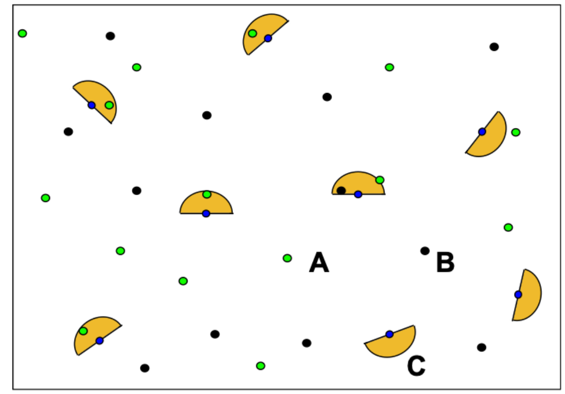
Egalitarian Social Learning (ESL)

- Not just the champion, but anyone can have useful knowledge.
- Learn from any other agent's success in specific situations.
- Training examples from the entire population culture.
- Promote diversity by dividing population into species (or subcultures).



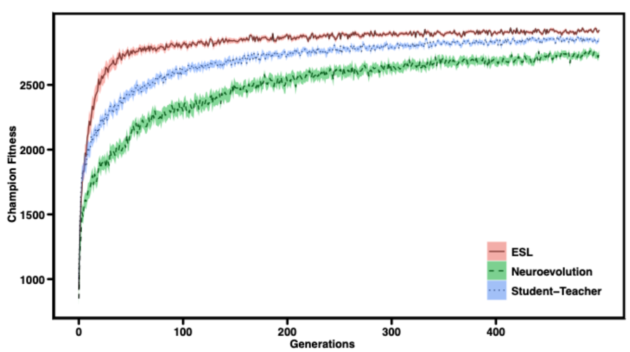
Foraging Domain Example

- Agents have limited view, variable speed, and forage for food that vary in value (good, bad, poison)
- Different strategies evolve: move a lot / don't miss anything,
- If an agent receives a low reward when another receives a high reward in the same situation, learn.



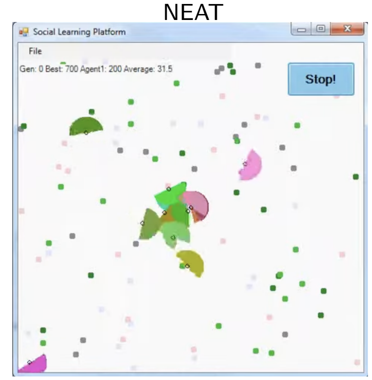
Results from ESL in Foraging Domain

- Good ideas propagate (e.g. slowing down not to miss)
- ESL learns faster than direct neuroevolution and student-teacher approach.
- Demonstrates value of diversity and social learning.
- A life lesson! Diverse teams perform better.



Demo of NEAT vs. ESL

NEAT



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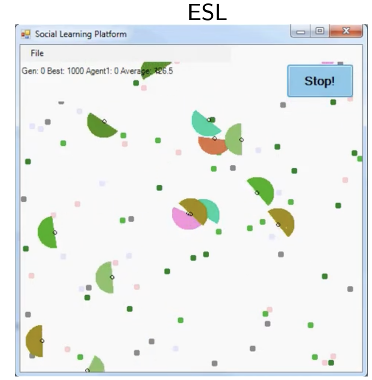
ESL



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Conclusion: The Importance of Diversity in Evolutionary Computation

- Why Diversity Matters:
  - Diversity is essential for robust and adaptive search in evolutionary computation.
  - It prevents premature convergence, enhances exploration, and enables discovery of better and more creative solutions.
- Methods work at different levels: genetic, behavior, ensembles, population; culling, selection, discarding, teaching; objectives, ensembles; can be combined?
- Analogies to biology, society.