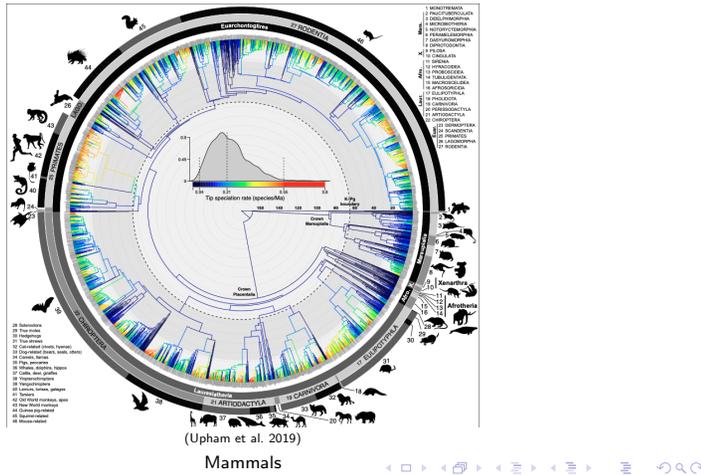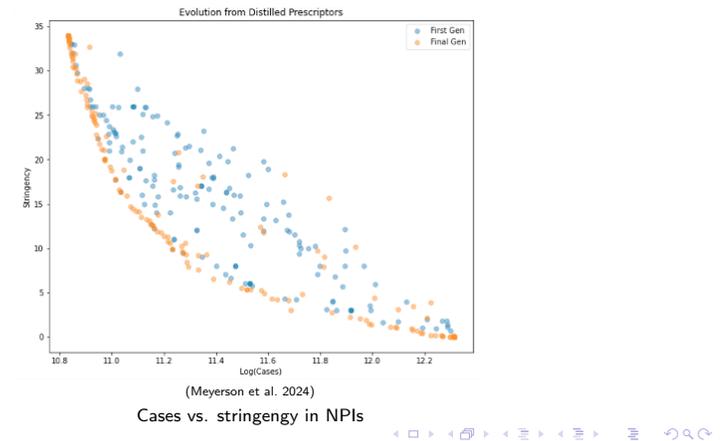## Multiobjective Optimization in Evolution

- ▶ 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.


(Upham et al. 2019)

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.

(Meyerson et al. 2024)

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.

(Meyerson et al. 2024)
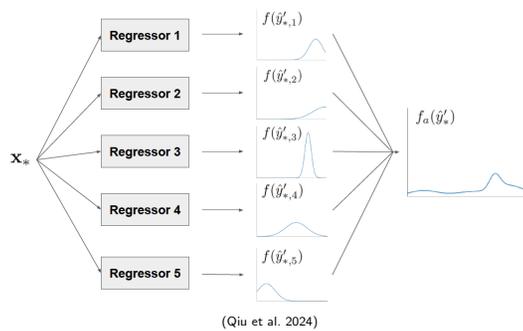
Cases vs. stringengy in NPIs
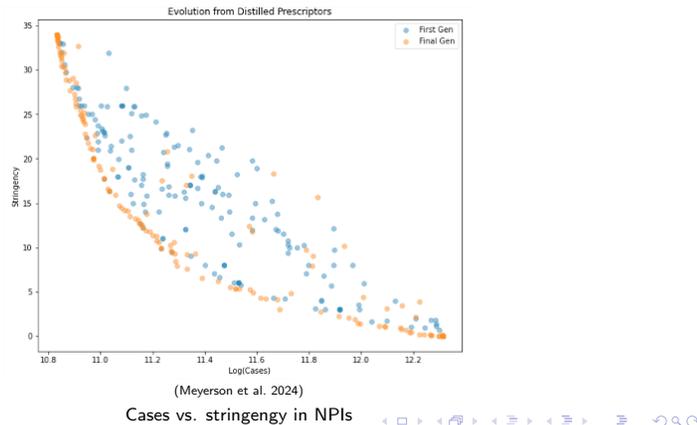
Boosting Diversity through Multiobjectivity

- ▶ 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.

(Meyerson et al. 2024)
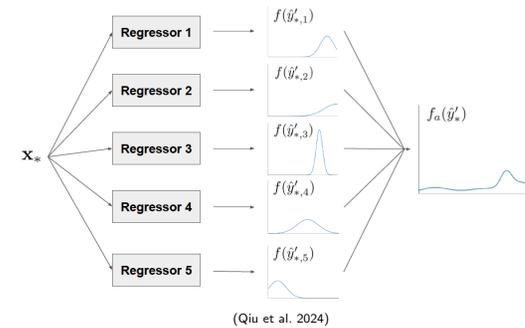
Cases vs. stringengy in NPIs
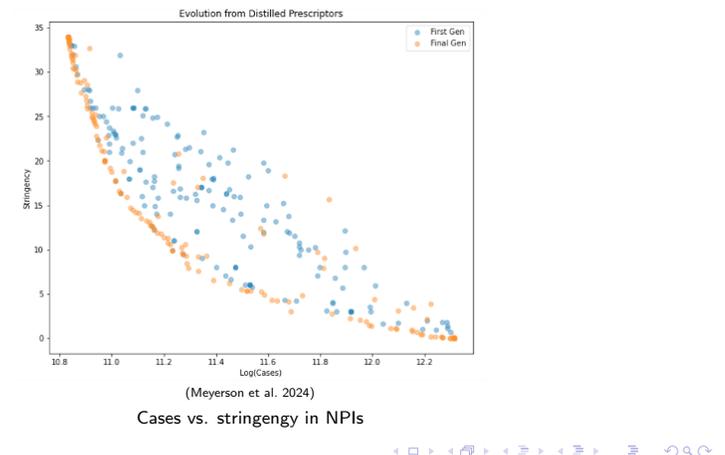
Ensembling Diverse Solutions

- ▶ 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

$\mathbf{x}_*$ — Regressor 1, Regressor 2, Regressor 3, Regressor 4, Regressor 5 — $f(\tilde{y}'_{*,1})$, $f(\tilde{y}'_{*,2})$, $f(\tilde{y}'_{*,3})$, $f(\tilde{y}'_{*,4})$, $f(\tilde{y}'_{*,5})$ — $f_a(\tilde{y}'_*)$

(Qiu et al. 2024)

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.

$\mathbf{x}_*$ — Regressor 1, Regressor 2, Regressor 3, Regressor 4, Regressor 5 — $f(\tilde{y}'_{*,1})$, $f(\tilde{y}'_{*,2})$, $f(\tilde{y}'_{*,3})$, $f(\tilde{y}'_{*,4})$, $f(\tilde{y}'_{*,5})$ — $f_a(\tilde{y}'_*)$

(Qiu et al. 2024)

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.

Evolution from Distilled Prescriptors

(Meyerson et al. 2024)
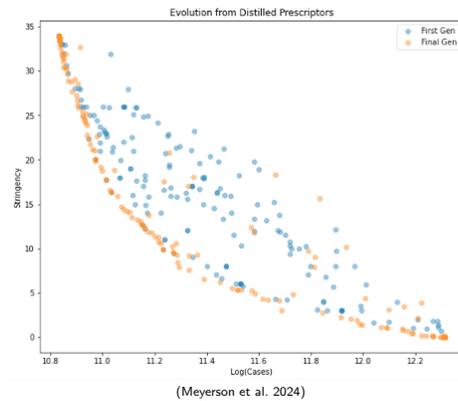
NEAT and Speciation in Ensembling

- ▶ 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.

Species

(Stanley & Miikkulainen 2002)
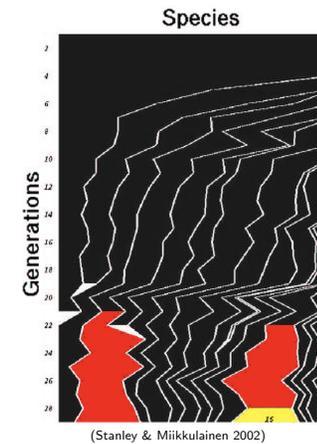
Ensembling Through Confidence Estimates

- 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.


(Schrum & Miikkulainen 2016)
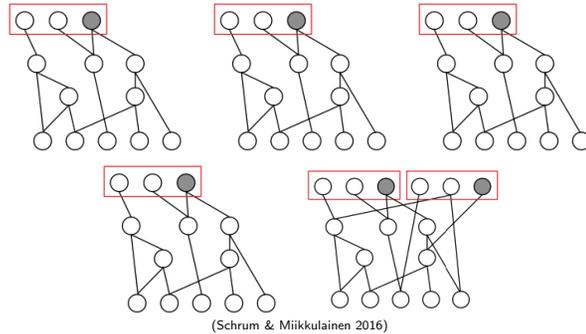
Ensembling Through a Gating Network

- 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.

(Zhou 2012)
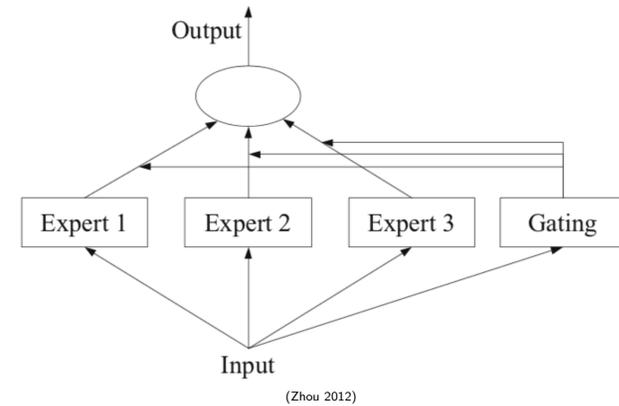
Ensembling Through a Gating Network

- 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.

(Pardoe et al. 2005)
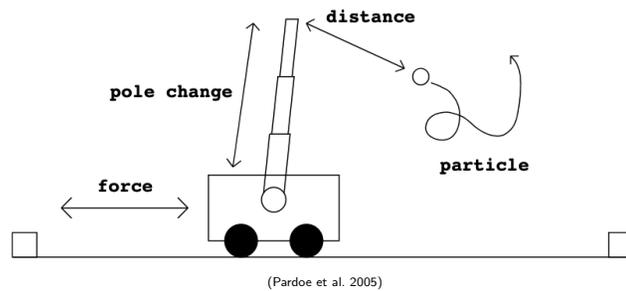
Gated Ensembling Example

- 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.

(Pardoe et al. 2005)
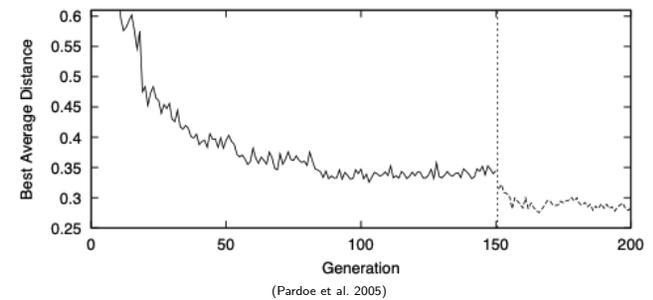
## Ensembling in Enforced Sub-Populations

- ▶ 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.

(Gomez 2003)
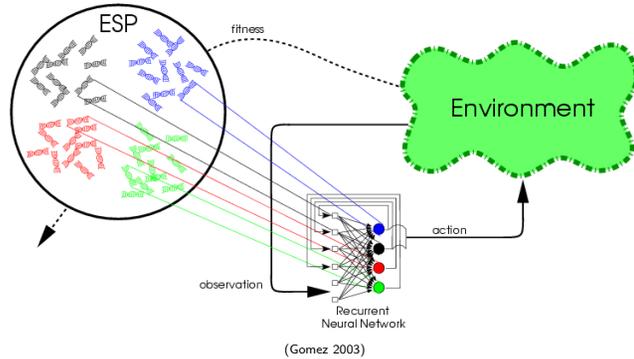
Hierarchical ESP

- ▶ 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.
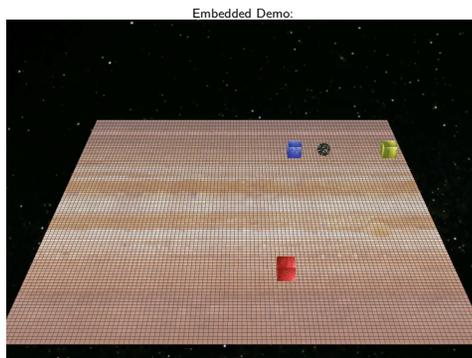 - ▶ E.g. a team of predators capturing a prey:
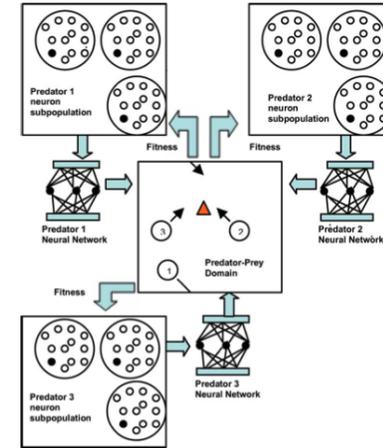
(Rawal et al. 2010)

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.

Embedded Demo:

(https://nn.cs.utexas.edu/?armsrace)

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 advantage 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.
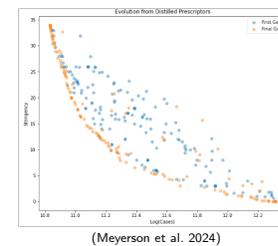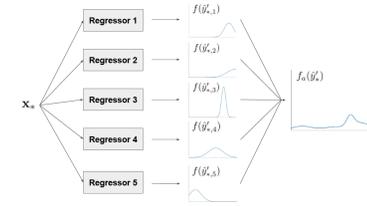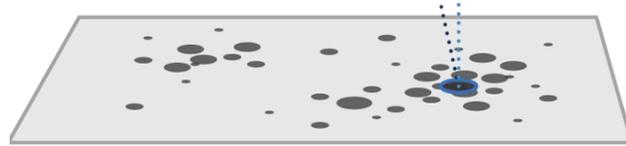

(Meyerson et al. 2024)   (Qiu et al. 2025)

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...
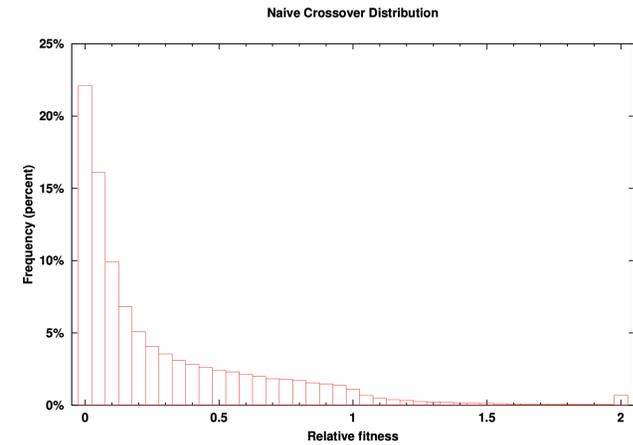
(Miikkulainen & Forrest 2021)

Culling: Speeding up Evolution

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

Naive Crossover Distribution

(McQuesten & Miikkulainen 1997)

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:

Perfect Culling Distribution
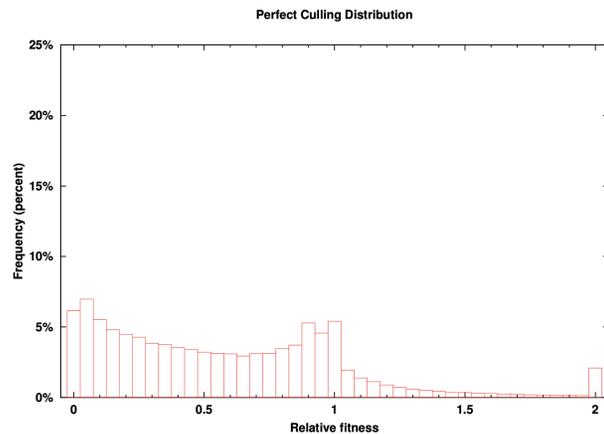
(McQuesten & Miikkulainen 1997)

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:

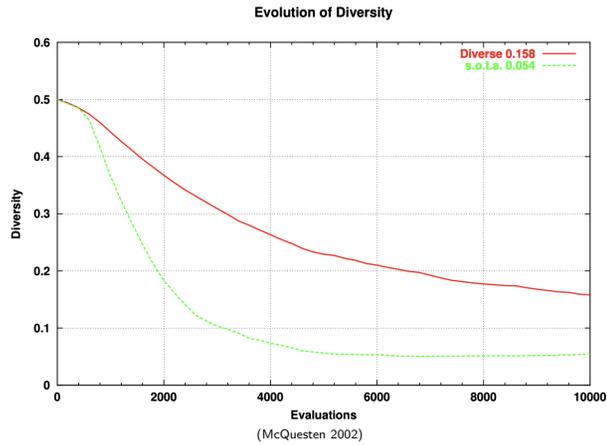**Distribution of relative fitness of offspring**

40 MATE 0.82
SOTA 0.85
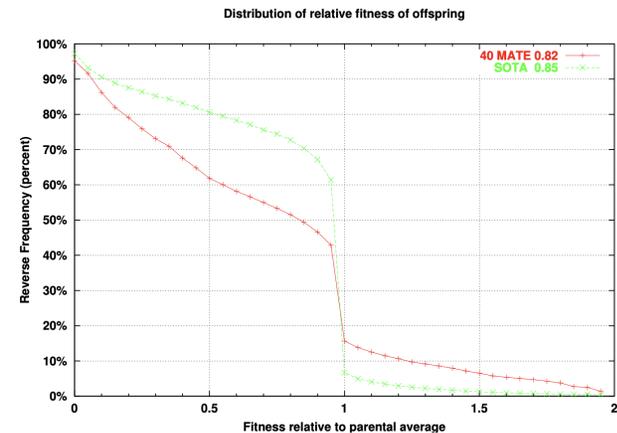
(McQuesten 2002)

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%.

(McQuesten 2002)

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?
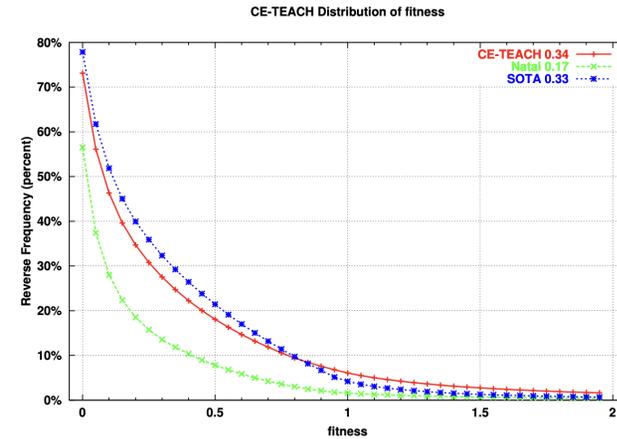
(McQuesten 2002)

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.
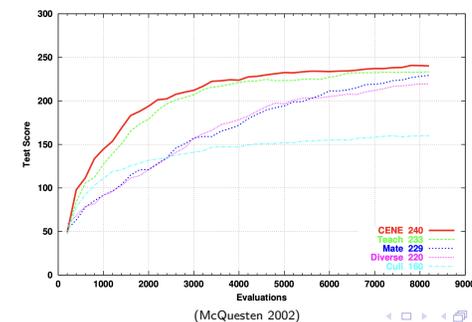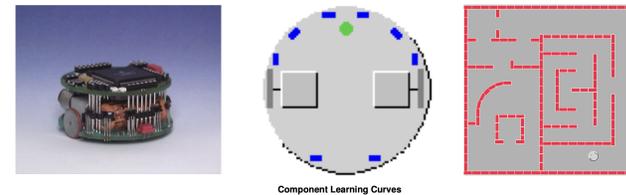- ▶ Solutions are more robust and more effective.
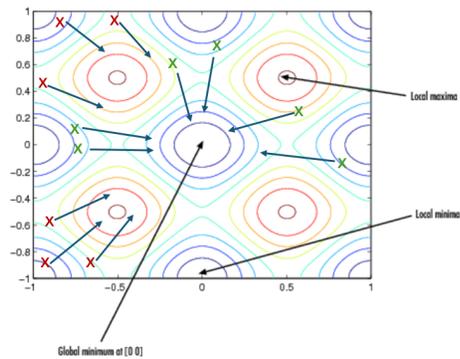
(Adapted from Najem & Yusif 2018)

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.
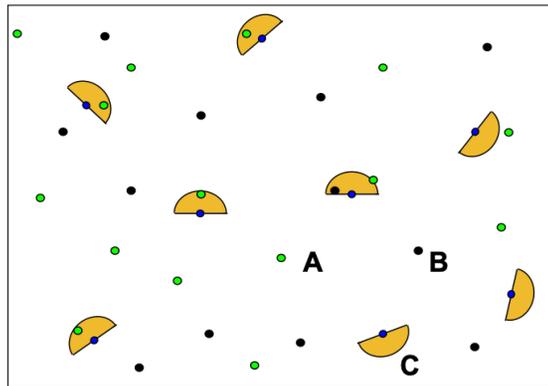- ▶ E.g. the simulated Khepera maze running task:

(McQuesten 2002)

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).

(Tansey et al. 2012)

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.
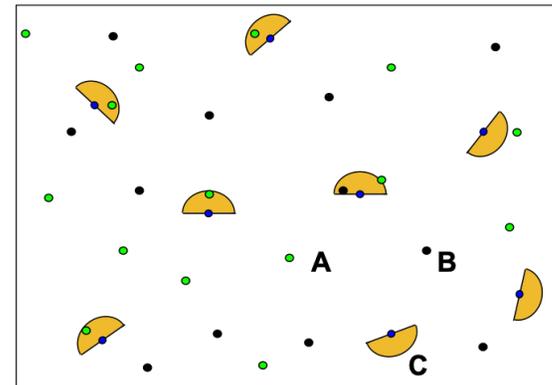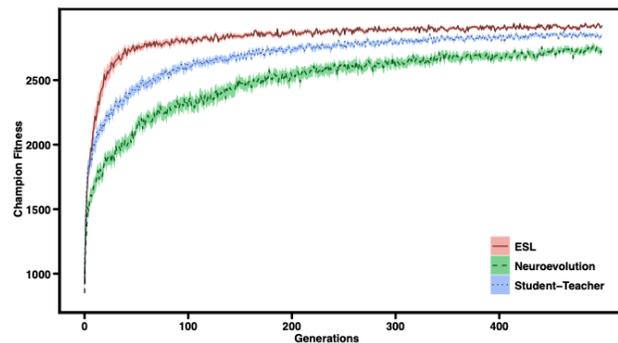

(Tansey et al. 2012)

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.

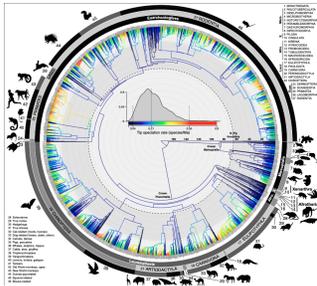(Tansey et al. 2012)

Demo of NEAT vs. ESL

NEAT

Demo link:
https://youtu.be/M5i-lWDNeH8

ESL

Demo link:
https://youtu.be/o0-kWNabCq8

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.

(Upham et al. 2019)

(https://youtu.be/o0-kWNabCq8)