

pAInball

Creating an AI to play Pinball

Spiros Bontomitsidis

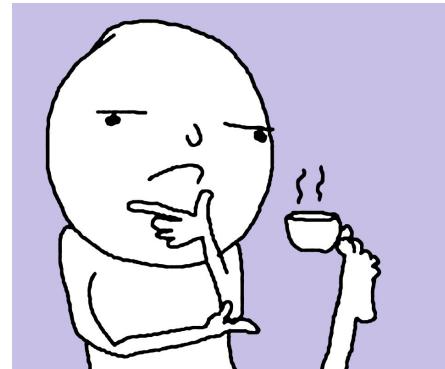
 [G-H](#) |  [L-IN](#) |  [E-M](#)

May 31st '24

The “problem” (and the motivation)

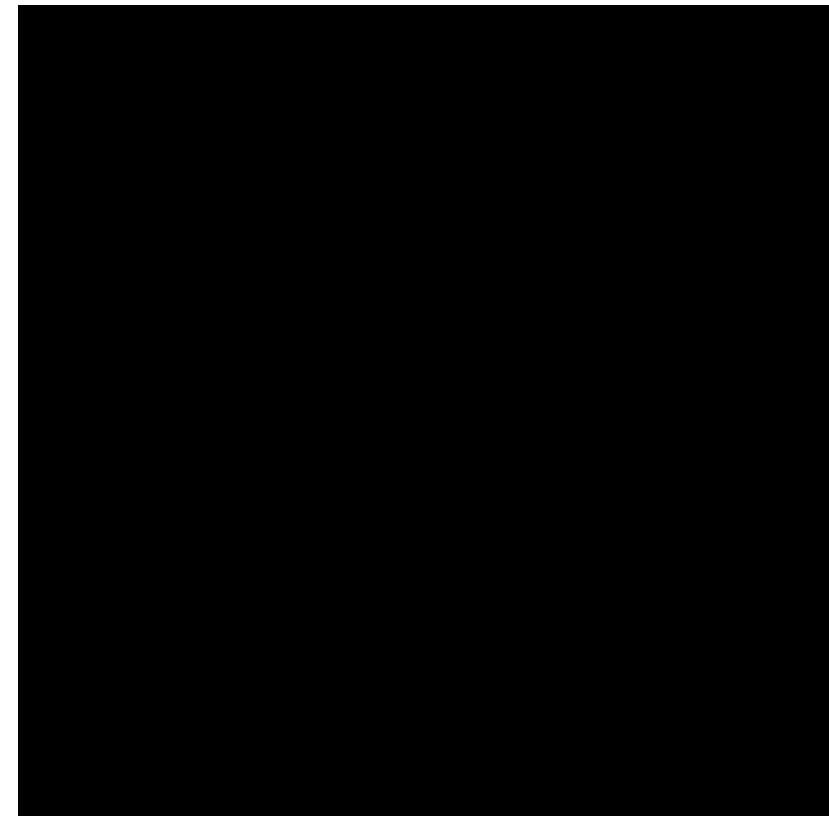
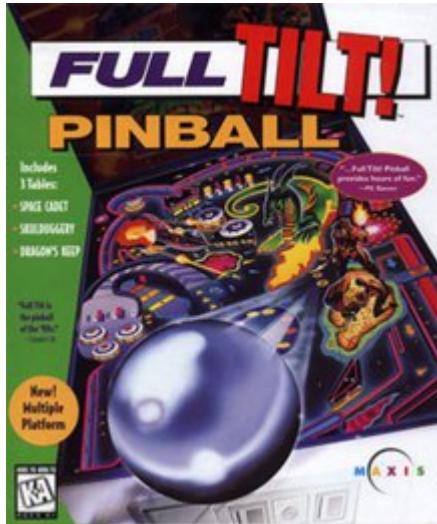
How can I learn about ML and Neural Networks...

...while I play video games?



The Game: Space Cadet

- Win95 and XP: 3D Pinball
- Developed by: Cinematronics/Maxis
- Decompiled! [Source available](#)



The AI: Training approach

Option 1: Teacher

- Record my gameplay
- Supervised Learning
- Gradient decent
- Back propagation



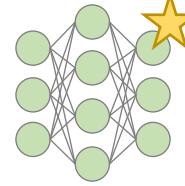
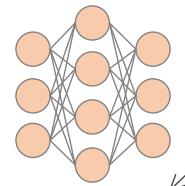
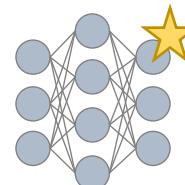
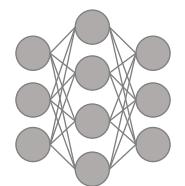
Option 2: God

- I make the rules!
- Genetic Algorithm: NEAT
- NeuroEvolution
- Imitates natural selection

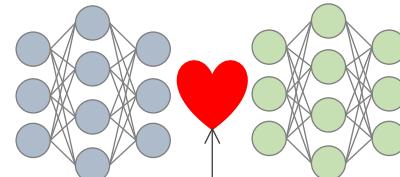


The AI: “Compete-Kiss-Repeat”™

Generation
of **N** Players



Mate the **k**
best



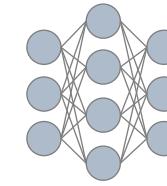
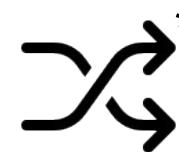
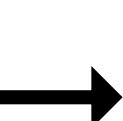
Fitness

Crossover

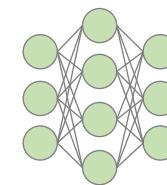
Make 1 child
(Crossover)

Seed Child

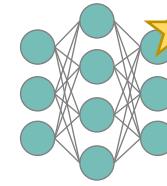
Mutations



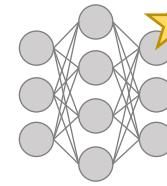
Parent 1



Parent 2



Seed Child



Fitness

Repeat

The AI: Game Outputs

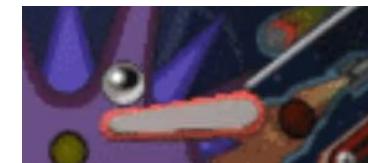


For NN Inputs:

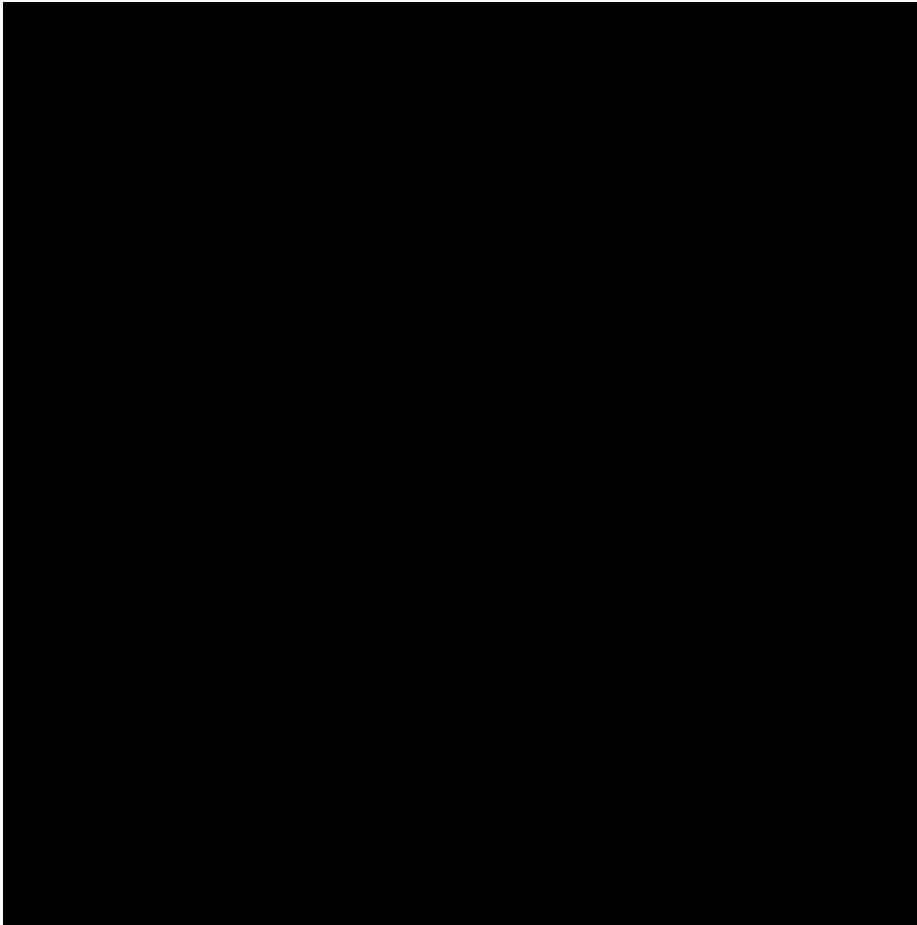
- Position (X, Y)
- Speed (V)
- Direction (V_x, V_y)

For Fitness:

- Score
- Lost Balls
- Ball Hits Left
- Ball Hits Right



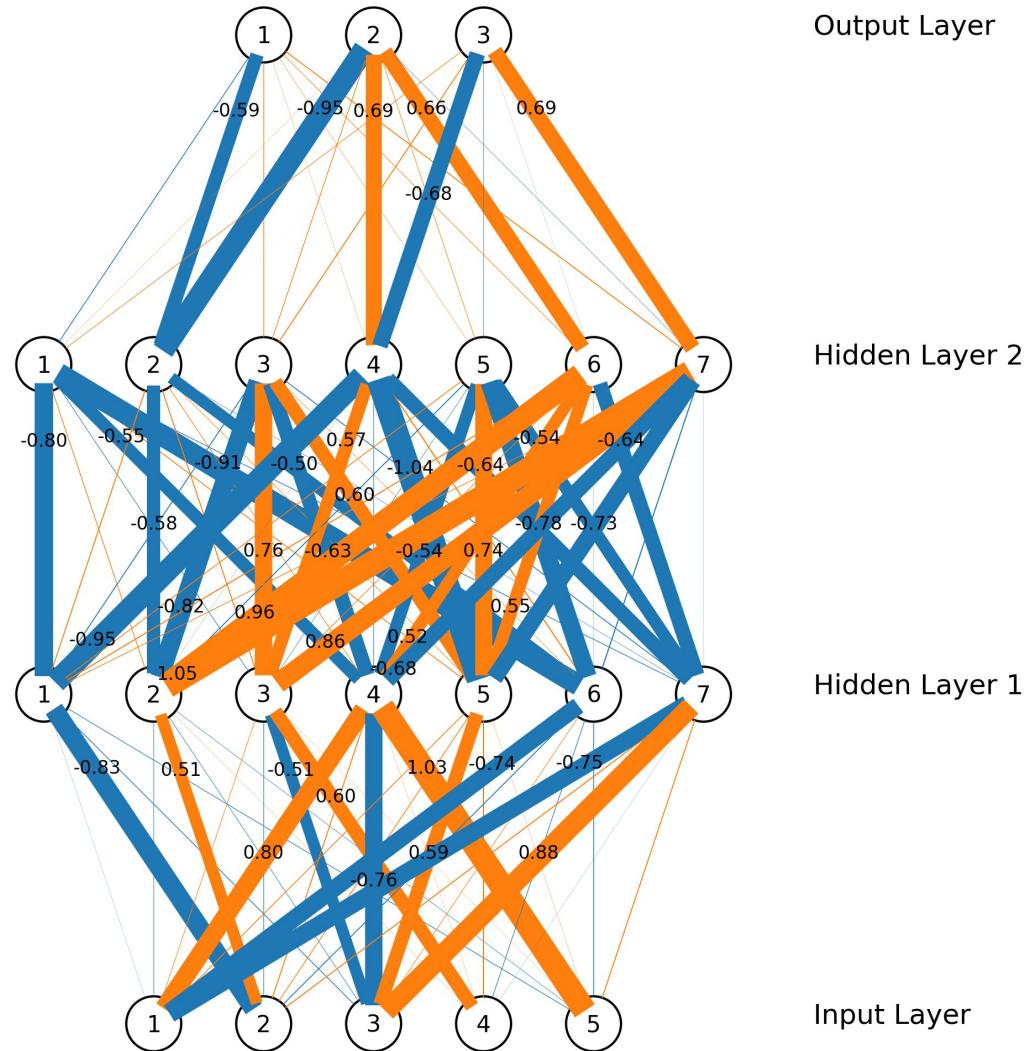
The AI: NN Outputs



- Do nothing
- Left Hit
- Right Hit

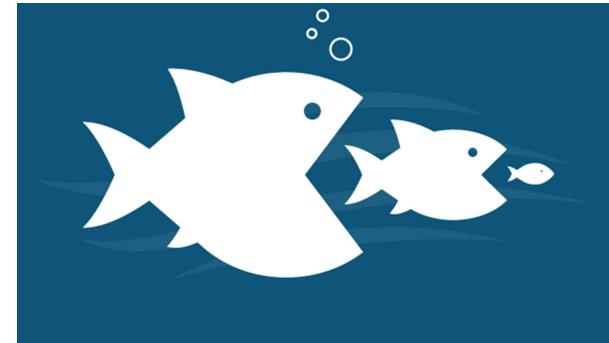
Final NN Shape

1-No Action 2-Left Hit 3-Right Hit



1-Speed 2-PosX 3-PosY 4-DirX 5-DirY

Survival of the fittest



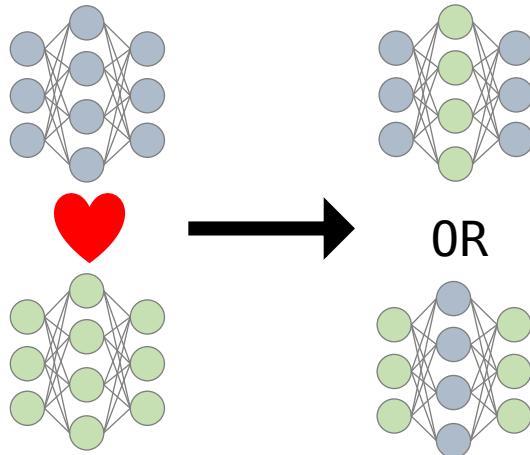
$$\text{Fitness} = \frac{\text{Score} + (\text{Ball_Hits_Left} + \text{Ball_Hits_Right}) \times 10\,000 - \text{Lost_Balls} \times 50\,000}{\text{Game Duration}} \times \text{mult},$$

where $\text{mult} \begin{cases} 2: \text{IF } \text{Ball_Hits_Left} > 0 \text{ AND } \text{Ball_Hits_Right} > 0 \\ 1: \text{Otherwise} \end{cases}$

Cross-Over Techniques

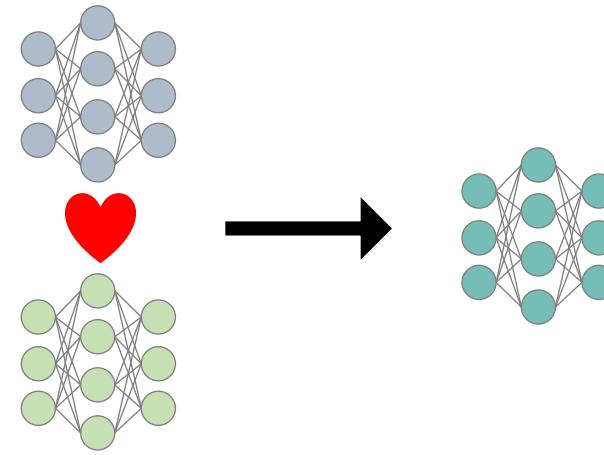


Layer Shuffle



```
def crossover_shuffle(self, parents: [NeuralNetwork]):  
    n_of_parents = len(parents)  
    child = copy.deepcopy(parents[0])  
    n_of_layers = len(child.layers)  
    parent_id = 0  
  
    for i in range(n_of_layers):  
        parent_id = i % n_of_parents  
        child.layers[i] = parents[parent_id].layers[i]  
        parent_id += 1  
    return child
```

Weight Average



```
def crossover_average(self, parents: [NeuralNetwork]):  
    n_of_parents = len(parents)  
    child = copy.deepcopy(parents[0])  
    n_of_layers = len(child.layers)  
  
    for i in range(n_of_layers):  
        avg_layer_weights=np.zeros(  
            np.shape(parents[0].layers[i].synaptic_weights)  
        )  
        for j in range(n_of_parents):  
            avg_layer_weights += np.array(  
                parents[j].layers[i].synaptic_weights  
            )  
        avg_layer_weights = avg_layer_weights / n_of_parents  
        child.layers[i].synaptic_weights = avg_layer_weights  
  
    return child
```

Mutation Techniques



- Given a Mutation probability: p_m (ex. 9%)

Offset

$$Weight = Weight + offset$$

$$offset \in [-0.1, 0.1]$$

Scale

$$Weight = Weight \times scale$$

$$scale \in [0.9, 1.1]$$

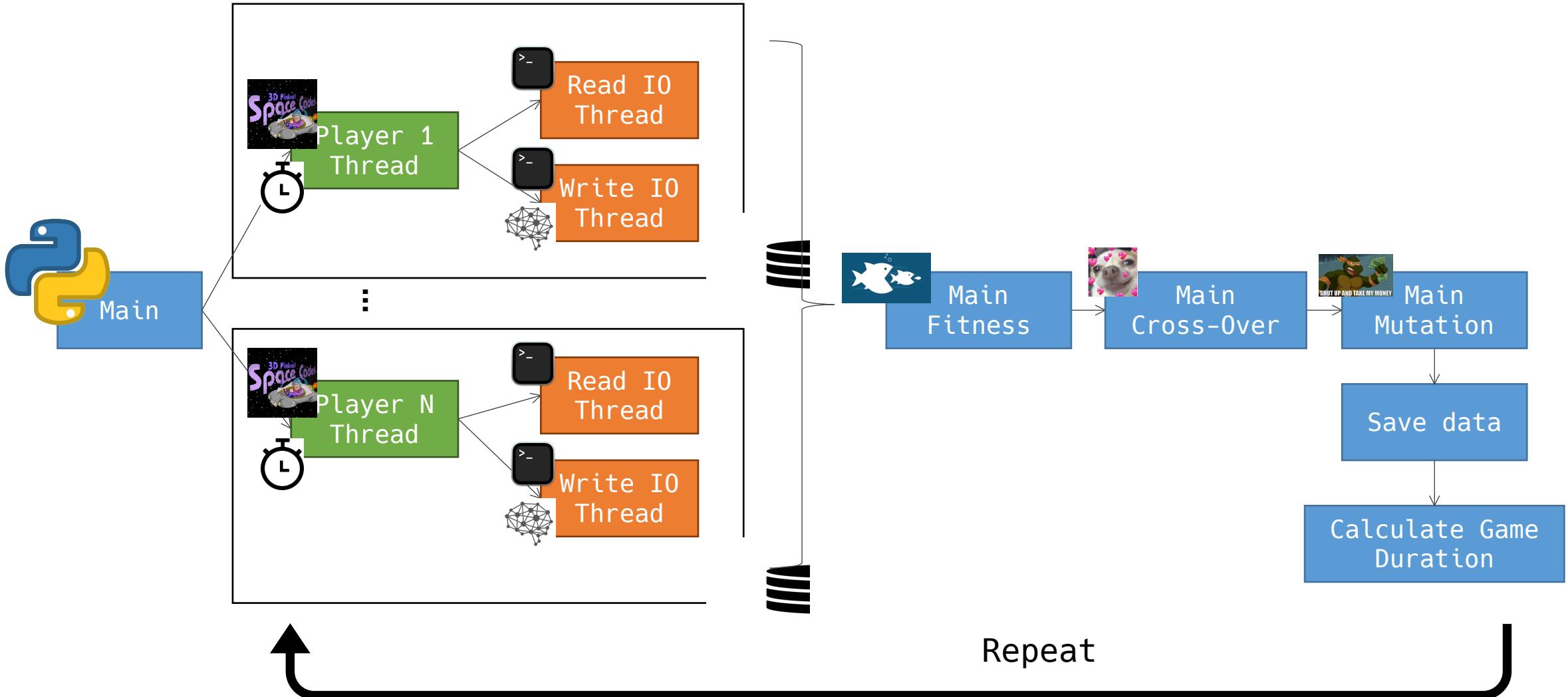
- Offset probability: $\frac{p_m}{3}$
- Scale probability: $\frac{2 \times p_m}{3}$

```
def mutate(self, child, prob_mut):
    mutant = copy.deepcopy(child)
    for idx, layer in enumerate(child.layers):
        for idy, weights in enumerate(layer.synaptic_weights):
            for idz, weight in enumerate(weights):

                random_number = random.random()
                if random_number < (prob_mut / 3):
                    mutant.layers[idx].synaptic_weights[idy][idz] += random.uniform(-1, 1) / 10
                elif random_number < prob_mut:
                    mutant.layers[idx].synaptic_weights[idy][idz] *= 1 + random.uniform(-1, 1) / 10

    return mutant
```

Game with Player Integration



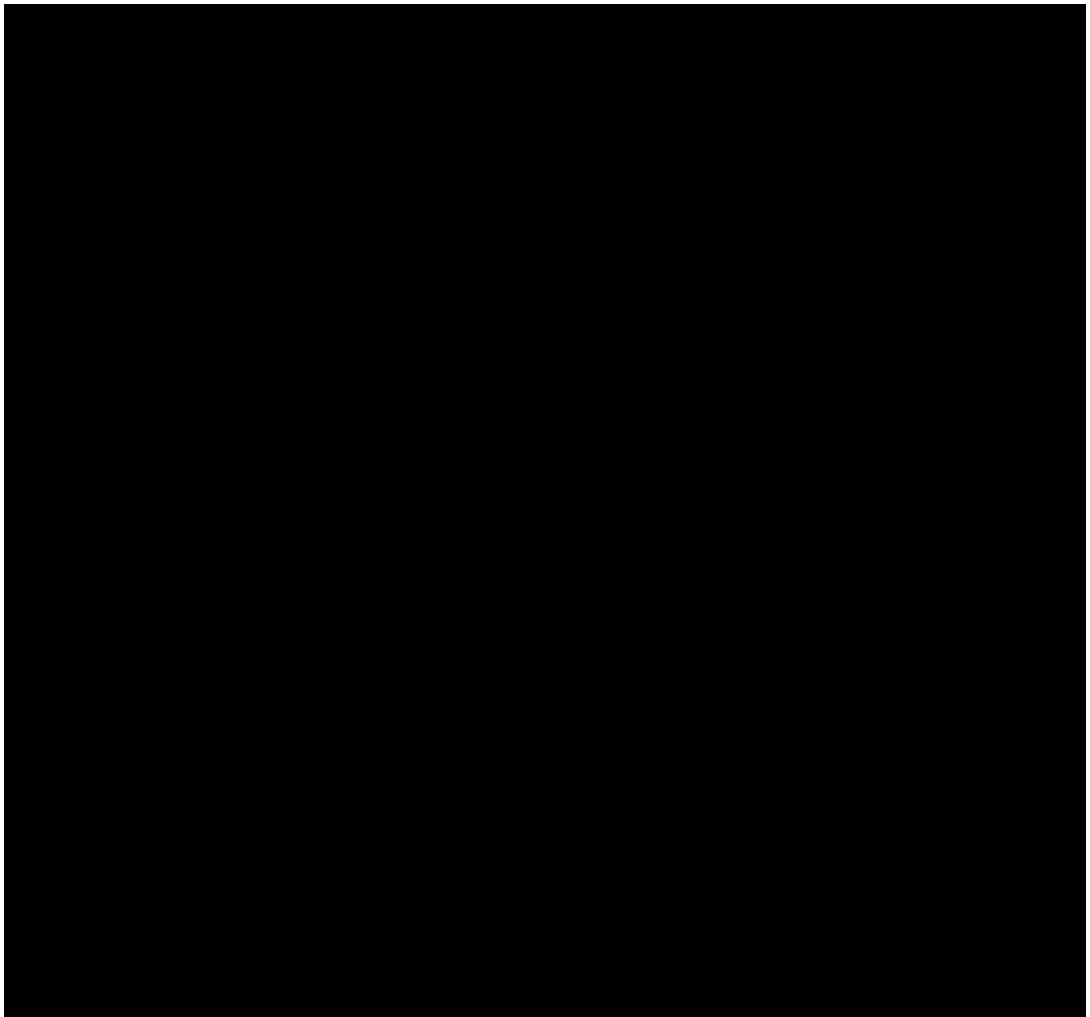
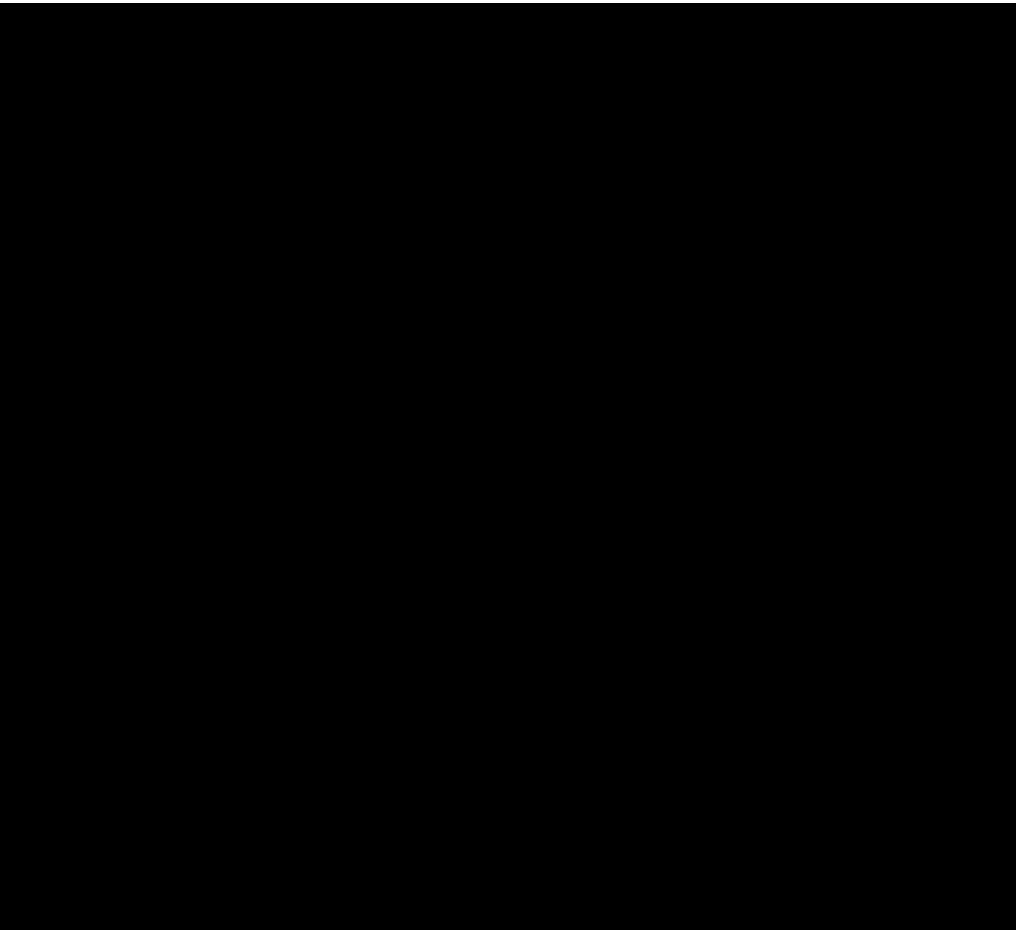
Player/Game STUDIO



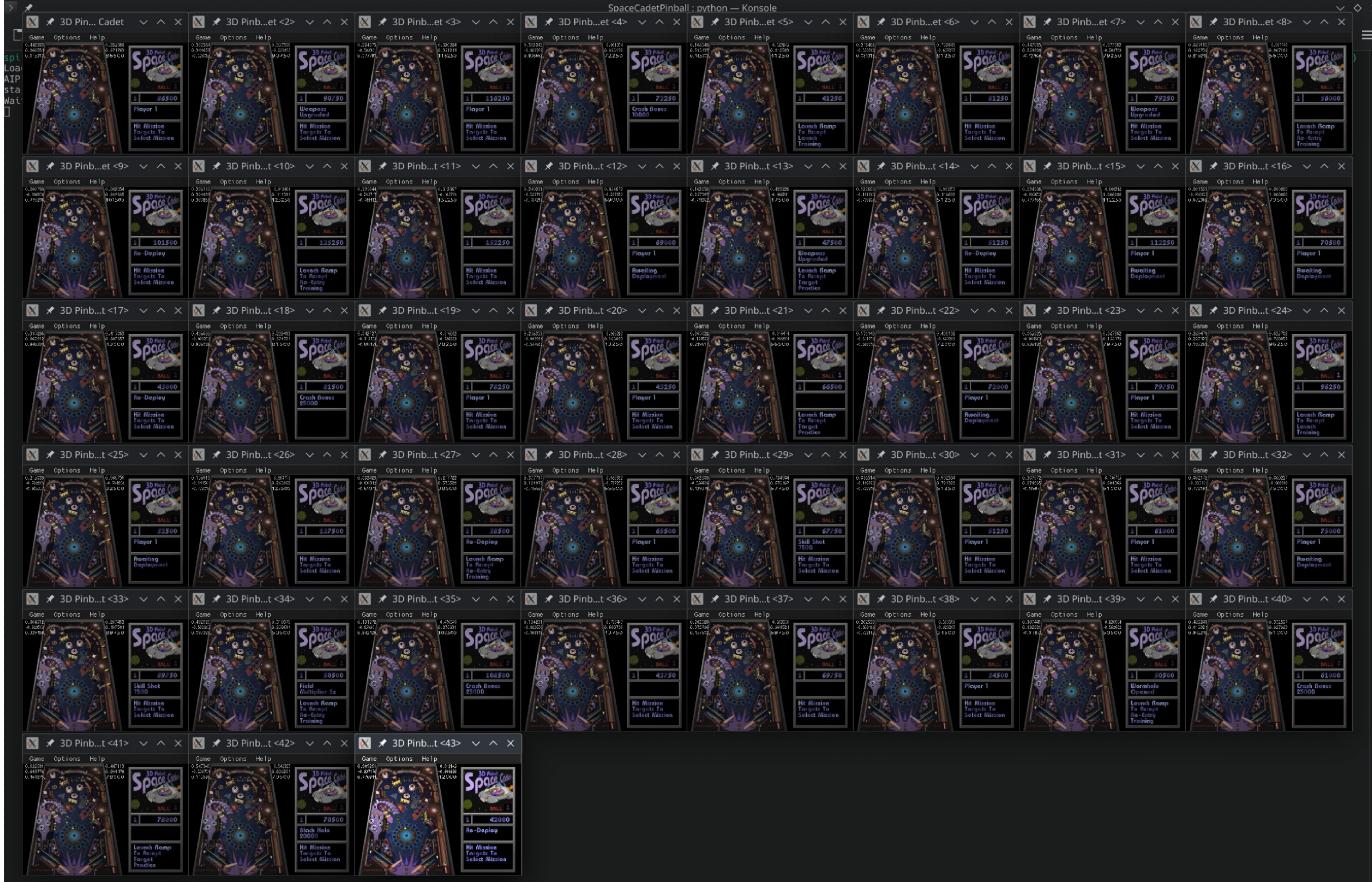
Read IO
Thread



Write IO
Thread



Live trAIning in action...



->link

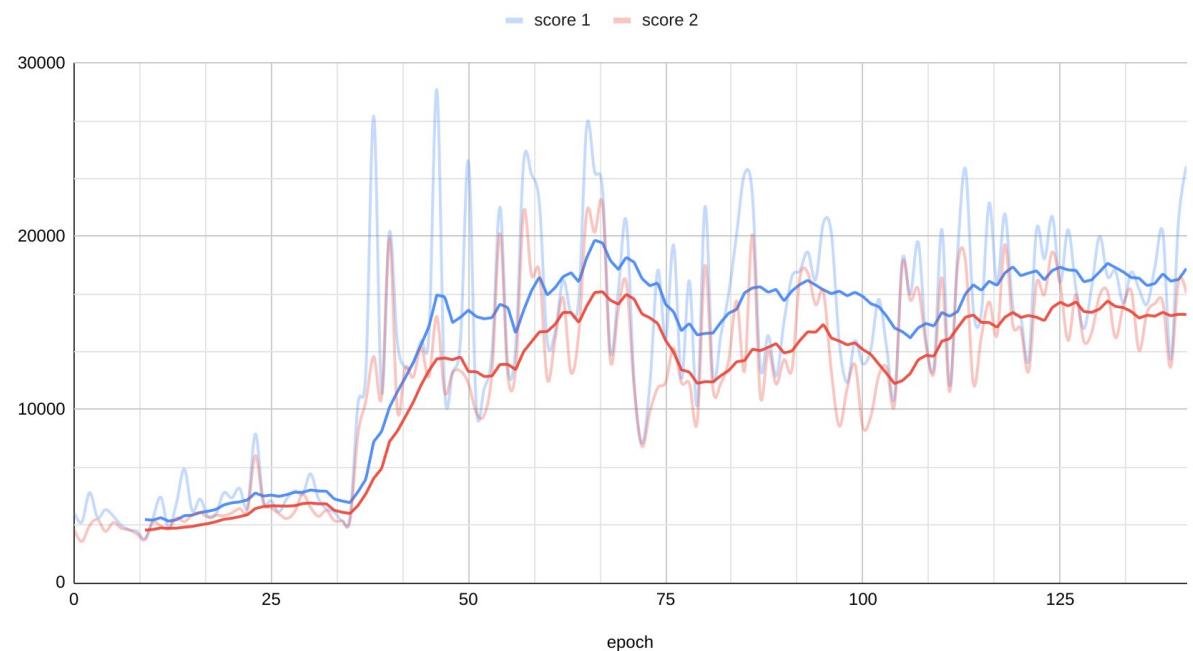
#Parents
2-Parents

Crossover

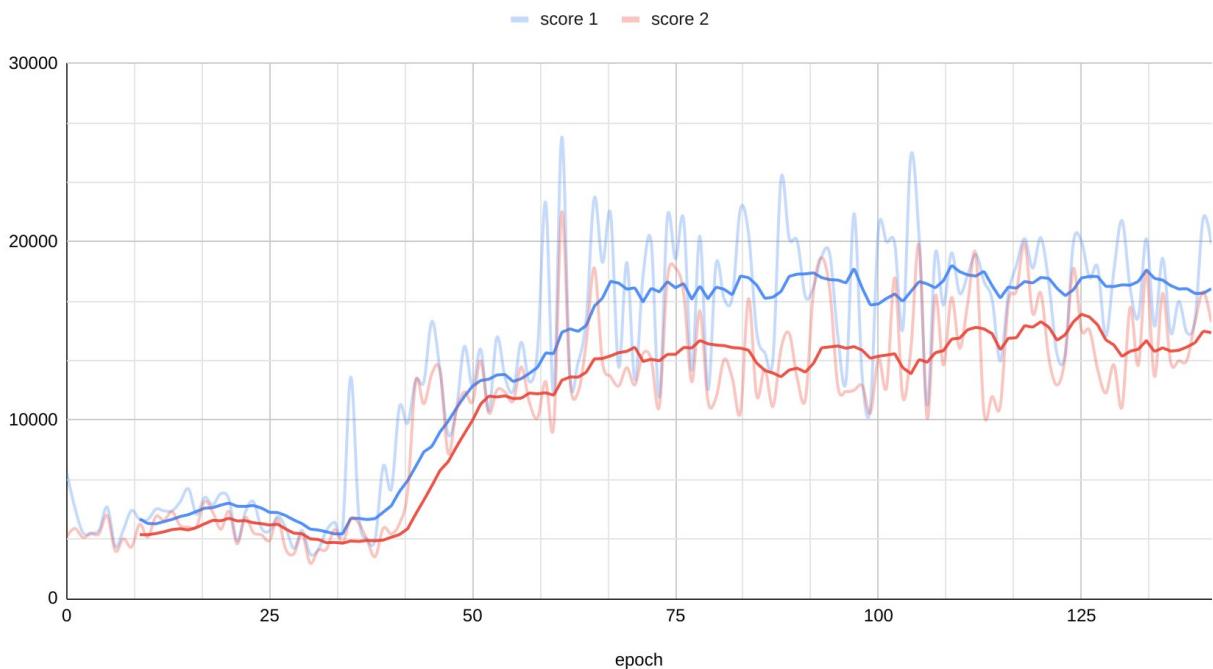
Mutation

Mutation
6% Scale

2-Parent Shuffle

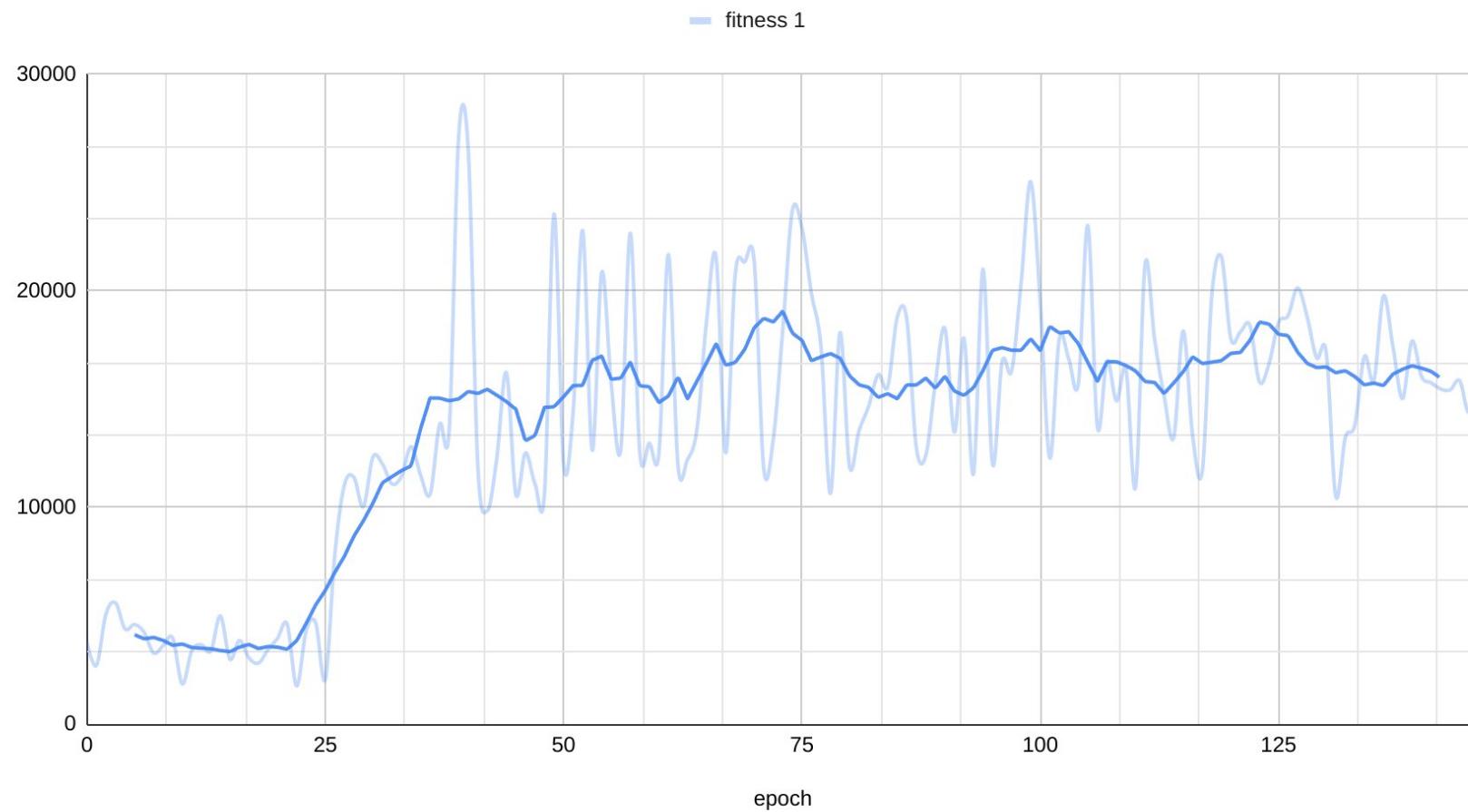


2-Parent Average



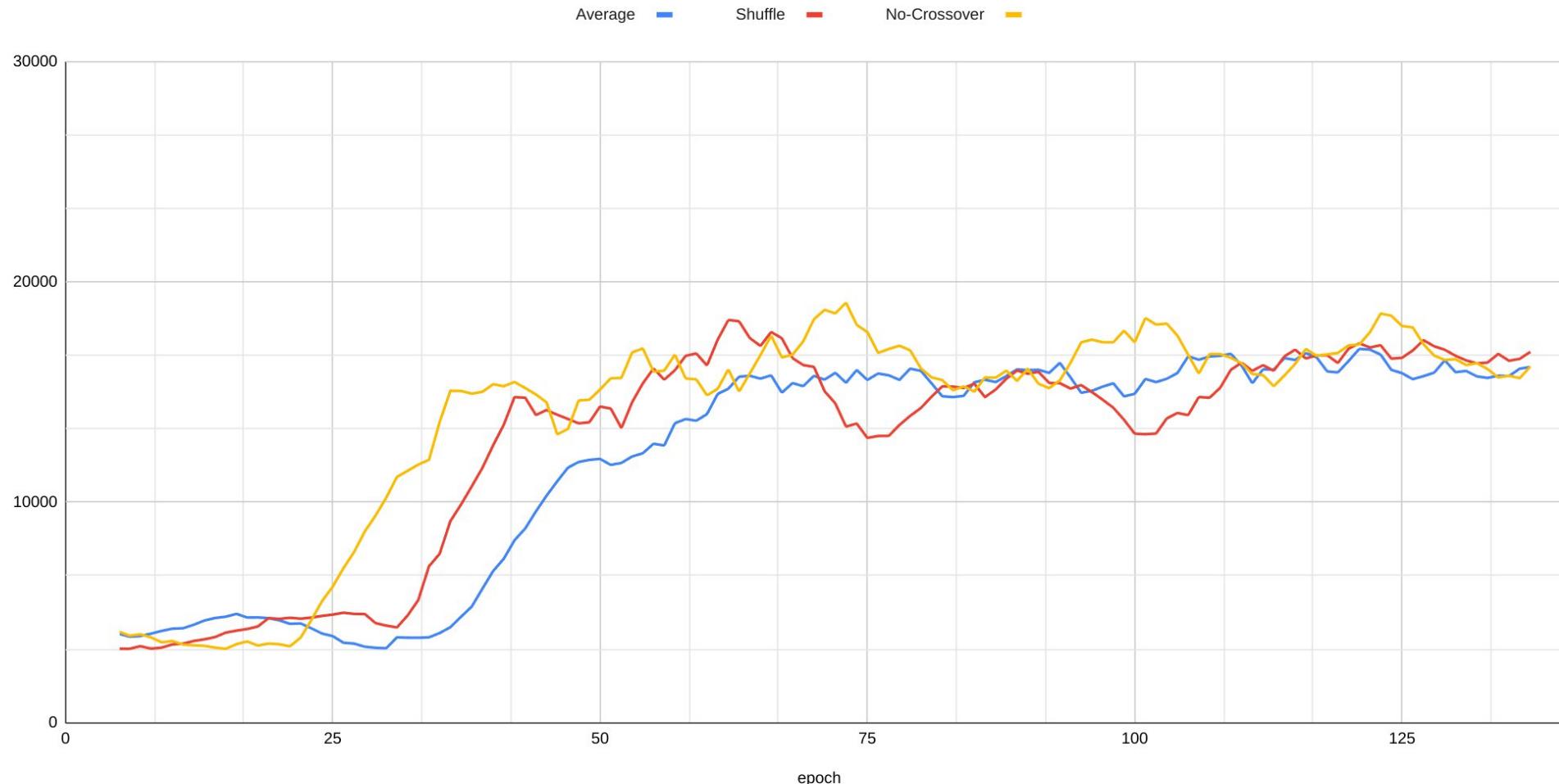
#Parents	Crossover	Mutation	Mutation
1-Parent	N/A	3% Offset	6% Scale

Single Parent - No Crossover



Crossover Comparison

Crossover comparison



Insights and Results

- NeuroEvolution is slow
- Spawning a few random NNs at every epoch helps in the beginning
- Cross-over function can be very complex to design and predict
- Go easy on mutations
- No crossover and only mutations ($k=1$) also leads to capable NNs

Thank you

Questions?

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 [G-H](#) |  [L-IN](#) |  [E-M](#)

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References/Links

- GitHub Repo: [pAInball](#)
- Space Cadet port: [k4zmu2a/SpaceCadetPinball](#)
- Library for Neural Network Visualization: [jzliu-100/visualize-neural-network](#)
- Multilinear NN example: [miloharper/multi-layer-neural-network](#)
- Genetic Algorithm for optimizing a NN: [luaffjk/ga-mlp](#)
- [Neuroevolution of augmenting topologies](#)