**AI assignment 2 - CT421 - Report**

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**Part 1**

**Analysis of Evolved Strategies**

In my experiment, I evolved strategies for the Iterated Prisoner’s Dilemma (IPD) using a genetic algorithm. Each evolved strategy is represented by a three‑gene genome that controls:

* **Initial Move:** The probability of cooperating on the first move.
* **Response to Cooperation:** The probability of cooperating after the opponent cooperates.
* **Response to Defection:** The probability of cooperating after the opponent defects.

For example, one of the best strategies I observed had a genome such as [0.96, 0.00, 0.41]. This indicates that the strategy almost always begins by cooperating; however, it tends to defect after the opponent cooperates (gene value of 0.00) while showing about a 41% likelihood to cooperate after a defection. This behaviour can be interpreted as a rather exploitative approach—taking advantage of overly cooperative opponents while still mitigating losses against defectors.

I noticed that the limited strategy space (only three parameters) led to rapid convergence. Within just a few generations, the genetic algorithm was able to identify high-performing strategies, and further evolution yielded only minor improvements. This shows that even with a simple representation, the algorithm is capable of discerning effective behaviours in the IPD.

**Performance Against Fixed Strategies**

I evaluated the performance of the best evolved strategy against three fixed opponents:

* **Always Cooperate:**  
  The evolved strategy scored very high (e.g., around 998 points) against Always Cooperate. It was able to exploit the naïve nature of this opponent effectively, resulting in a significant payoff differential.
* **Always Defect:**  
  Against Always Defect, both the evolved strategy and its opponent achieved low scores (e.g., around 1 point each). In this case, the evolved strategy learned to retaliate when faced with constant defection, minimizing any potential exploitation.
* **Tit-for-Tat:**  
  In matches against Tit-for-Tat, the outcome was balanced (for instance, both receiving about 322 points). This reflects a mutual tendency towards reciprocity, with the evolved strategy achieving a satisfactory balance between cooperation and defection.

**Discussion of Interesting Findings**

During my analysis, I observed several interesting points:

* **Rapid Convergence:**  
  One notable finding was how quickly the algorithm improved its best fitness within the first few generations. In my runs, the best fitness increased sharply in the early stages, reflecting that the search space was small, and the genetic algorithm could quickly pinpoint effective strategies.
* **Exploitation of Cooperation:**  
  It was particularly interesting that one of the best strategies evolved to defect following cooperation (gene value 0.00) despite starting with a high probability to cooperate. This suggests that, in the mix of opponents, being exploitative against the Always Cooperate strategy yielded higher payoffs, even when it might seem counterintuitive from a purely “cooperative” perspective.
* **Balanced Performance:**  
  The strategy’s balanced performance against a range of opponents—including tit-for-tat and always-defect—demonstrates its adaptability. Although the simple three-gene representation limits possible behaviours, the evolutionary process nonetheless captured a trade-off between building mutual cooperation and preventing exploitation.

**Visualization of Fitness Progression Over Generations**

**Figure 1: Fitness Progression**

A graph with blue and orange lines

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*In Figure 1, I show a line graph of both the best fitness and the average fitness over 50 generations. As you can see, the best fitness (blue line) increases rapidly early on and stabilizes after about 20–30 generations. The average fitness (orange line) follows a similar upward trajectory, albeit with less dramatic improvements, indicating that while the population is overall improving, only a subset reaches near-optimal performance.*

**Figure 2: Terminal Output and Strategy Analysis**

A computer screen shot of a program

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*Figure 2 is a screenshot of the terminal output summarizing the best strategy’s performance. This image includes the final fitness value of 1,464, the best strategy’s genome (e.g., [0.96, 0.00, 0.41]), and detailed scores against the fixed strategies (Always Cooperate, Always Defect, and Tit-for-Tat). The output serves as direct evidence of the strategy’s effectiveness and highlights how it adapts to different opponents.*

**Part 2**

**Methodology**

For this extension, I adopted a fully co-evolutionary framework where each strategy in the population competes against every other strategy rather than against a set of fixed opponents. The key elements of this approach are:

* **Population Initialization:**  
  I initialized a population of strategies, each represented by a genome of three values that determine:
  + The probability of cooperating on the initial move.
  + The probability of cooperating after observing an opponent’s cooperation.
  + The probability of cooperating after observing an opponent’s defection.
* **Game Dynamics and Noise:**  
  In each match (consisting of 200 rounds), strategies played the Iterated Prisoner’s Dilemma with the standard payoff matrix. I also introduced a parameter for noise—randomly flipping moves—to simulate errors or misinterpretations during play.
* **Evaluation through Co-evolution:**  
  Each individual strategy played against every other strategy in a round-robin tournament. Their fitness was calculated as the average score accumulated against all opponents.
* **Genetic Operators:**  
  I applied tournament selection, single-point crossover, and mutation to generate new populations. This iterative process was run for 50 generations, tracking the best fitness, average fitness, and population diversity over time.
* **Metrics:**  
  I monitored not only the fitness evolution but also population diversity, measured as the mean Euclidean distance between the genomes. This helped assess how converged or diverse the evolving strategies were throughout the process.

**Results**

**Fitness and Diversity Trends**

* **Fitness Evolution:**  
  Over the 50 generations, I observed that the best fitness showed a gradual increase, while the average fitness also improved, though at a lower rate. Early generations exhibited rapid gains as initial random strategies were quickly outperformed by emerging high-fitness individuals. By later generations, the best fitness values converged toward a plateau.
* **Population Diversity:**  
  The diversity metric started at a higher level (indicating a wide range of different strategies) and gradually decreased as the successful genes spread through the population. Despite this convergence, mutation and noise maintained a baseline diversity, preventing complete homogenization of the strategies.

A graph of different types of data

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*Figure 1 displays the fitness evolution and population diversity trends across generations.*

**Best Strategy Characteristics**

* The best evolved strategy from the co-evolutionary run had a genome that suggested a clear bias toward defection in the initial rounds (with a relatively low probability to cooperate as its first move) while still incorporating low, but nonzero, chances to cooperate after both cooperation and defection by opponents.
* The emergent behaviour from this strategy can be seen as a **“mixed strategy”**:
  + **Initial Move:** Lower probability of cooperation—indicating a cautious or even opportunistic start.
  + **After Cooperation:** Very low cooperation rates, suggesting that the strategy tends to exploit naive or overly cooperative opponents.
  + **After Defection:** A moderate chance of cooperation, indicating that while the strategy is generally defection-prone, it still occasionally seeks to return to mutual cooperation if the opportunity arises.

**Computational Efficiency**

* The 50-generation co-evolutionary run was efficient, completing in under 3 seconds. This rapid execution, even with a pairwise round-robin match setup, highlights the feasibility of exploring more complex or larger-scale experiments in future work.

**Terminal Output and Performance Summary**

The terminal output confirmed:

* **Final Best Fitness:** Approximately 577.76
* **Best Strategy Genome:** Roughly [0.32, 0.09, 0.23]
* **Runtime:** The simulation completed in under 3 seconds.

A screenshot of a computer

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*Figure 2 shows a screenshot of terminal outputs highlighting the best strategy’s performance and genome details.*

**Discussion**

Several interesting findings emerged from this co-evolutionary extension:

1. **Defection Bias in a Dynamic Population:**  
   Unlike fixed-opponent scenarios, the co-evolutionary setting encourages strategies to explore more exploitative behaviour. The best strategy’s lower probability of cooperating on the initial move and after cooperation indicates a tendency to pre-emptively guard against exploitation—a behaviour that becomes advantageous when all strategies are adapting simultaneously.
2. **Residual Cooperation as a Stabilizing Factor:**  
   Even though the strategies evolved with an overall bias toward defection, the presence of a moderate probability to cooperate after defection suggests that complete collapse into universal defection is avoided. This residual cooperation appears to help maintain occasional mutual cooperation, which can be a defensive mechanism against the worst-case outcomes of constant defection.
3. **Population Convergence and Diversity:**  
   The observed decline in population diversity over generations is expected as the gene pool is exploited by high-performing strategies. However, the continuous introduction of diversity through mutation and the presence of noise prevented complete convergence, allowing the evolutionary process to explore alternative adaptations even in later generations.
4. **Implications for Future Research:**  
   The results from this co-evolutionary experiment highlight the potential to refine strategy representations. Future extensions could include longer memory (e.g., memory-2 or memory-3 strategies) or continuous trait representations. Additionally, varying the noise level could further probe the robustness of emergent behaviours.

**Conclusion**

The co-evolutionary experiments provided valuable insights into how strategies adapt in a dynamic and competitive environment. In this extended setting, the evolved strategies shifted toward a more defecting approach while retaining a minimal level of cooperation to prevent mutually suboptimal outcomes. Overall, this extension confirms the power of genetic algorithms not only to evolve effective strategies in IPD but also to reveal subtle dynamics of adaptation under co-evolutionary pressure.