Experimental Report: Analysis of Differential Evolution Settings

This report documents the independent effects of various parameter settings used in Differential Evolution (DE) for model optimization. The experiments varied configurations such as mutation strategy, crossover strategy, selection method, population initialization, mutation factor (F), crossover rate (CR), and population size. Below is a breakdown of each setting and its observed impact on final test accuracy.

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1. Mutation Strategy

Tested Variants: mutation_best_1, mutation_rand_1

- Observations:
  - mutation_best_1 resulted in lower accuracies, ranging from 0.1754 to 0.5417.
  - mutation_rand_1 consistently outperformed the other strategy, with the highest accuracy reaching 0.7846.
- Conclusion:
  - mutation_rand_1 promotes better exploration and diversity, making it more suitable for this optimization problem.

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2. Crossover Strategy

Tested Variants: crossover_exponential, crossover_binomial

- Observations:
  - crossover_binomial produced significantly higher accuracies, up to 0.7846.
  - crossover_exponential lagged with best accuracy at 0.3288.
- Conclusion:
  - crossover_binomial is more effective in maintaining diversity and convergence.

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3. Selection Strategy

Tested Variants: select_tournament, select_better, Crowding

- Observations:

    - select_better yielded the best results overall, peaking at 0.7846.
    - Crowding achieved moderate results, up to 0.6554.
    - select_tournament showed varied but generally lower performance.
- Conclusion:
    - select_better offers a good balance between exploration and exploitation.

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4. Population Initialization

Tested Variants: random, gaussian

- Observations:
    - random initialization outperformed gaussian, reaching 0.7846.
    - gaussian showed moderate success, peaking at 0.3913.
- Conclusion:
    - random initialization leads to a more diverse initial population.

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5. Mutation Factor (F)

Tested Values: 0.5, 0.6, 0.7

- Observations:
    - F values of 0.5 and 0.6 produced the most stable and highest accuracies.
    - F = 0.6 reached up to 0.7250.
- Conclusion:
    - A mutation factor between 0.5 and 0.6 is optimal.

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6. Crossover Rate (CR)

Tested Values: 0.7, 0.9

- Observations:
    - High-performing runs used both 0.7 and 0.9, depending on other parameters.
- Conclusion:

- CR is not dominant alone but interacts with other settings.

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7. Population Size

Tested Sizes: 20, 30, 50

- Observations:
  - Increasing population size generally improved accuracy (e.g., 0.6963 at size 30).
  - However, size 50 did not outperform size 30, suggesting diminishing returns.
- Conclusion:
  - Moderate increase in population size enhances performance, but balance with computational cost is necessary.

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8. Best Configuration Identified

Parameter	Value
Mutation Strategy	mutation_rand_1
Crossover Strategy	crossover_binomial
Selection Strategy	select_better
Initialization	random
Population Size	20
Mutation Factor (F)	0.5
Crossover Rate (CR)	0.7
Generations	1500
Final Accuracy	**0.7846**

Conclusion

This set of experiments illustrates the significant impact that parameter configurations have on DE performance. In particular, mutation_rand_1 combined with crossover_binomial, select_better, and random initialization produced the most robust and accurate results. Future work could explore adaptive mechanisms to dynamically adjust these settings during evolution.