MDL Genetic Algorithm project report

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Overview of the Algorithm

The structure of our Genetic algorithm is the same as a normal Genetic Algorithm, but we have implemented a custom crossover function rather than a standard crossover function.

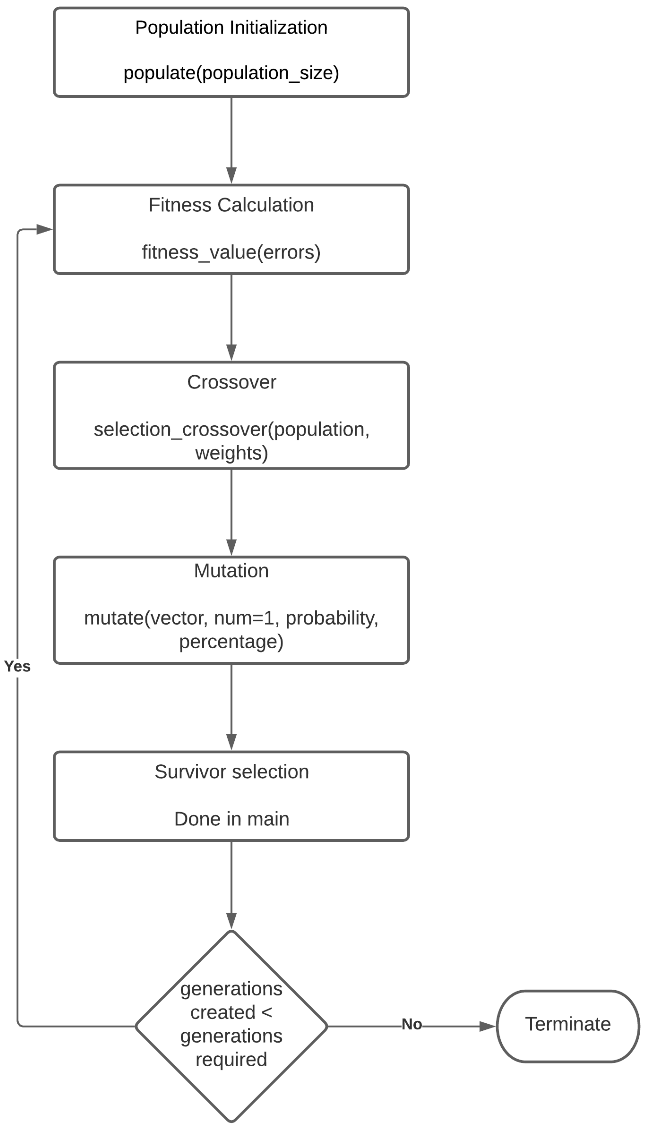

Population Initialization
populate(population_size)
Fitness Calculation
fitness_value(errors)
Crossover
selection_crossover(population, weights)
Mutation
mutate(vector, num=1, probability, percentage)
Yes
Survivor selection
Done in main
generations created < generations required
No
Terminate

Figure 1: Flowchart representing the Genetic Algorithm

Iterations

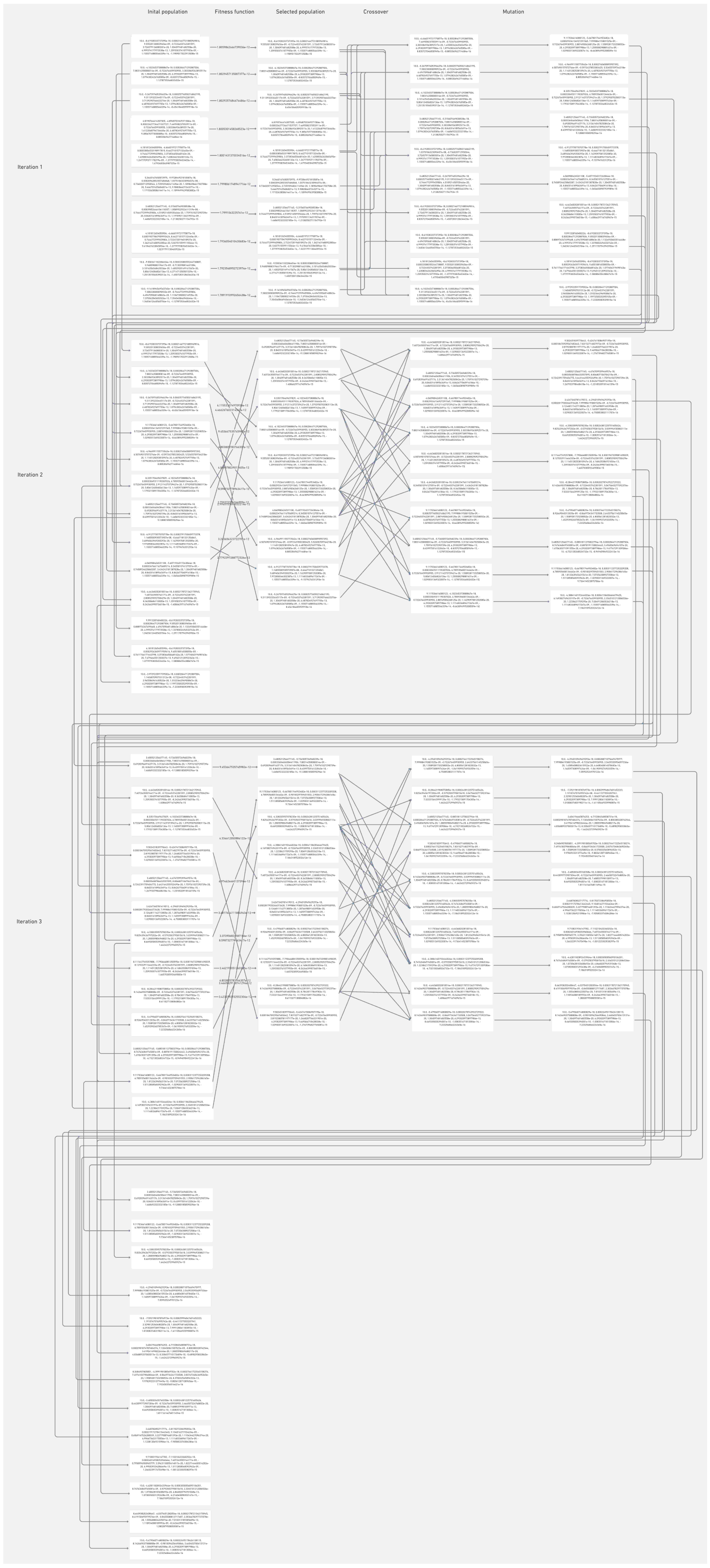


Figure 2: Diagram denoting running of algorithm for 3 iterations

Fitness function

We have calculated fitness for a vector using the formula:

$$\frac{1}{|(\text{train\_error x TRAIN\_FACTOR}) + (\text{validation\_error x TEST\_FACTOR}) + (|\text{train\_error - validation\_error}| \text{ x DIFF\_FACTOR})\ |}$$

We are using reciprocal of errors since minimizing errors should maximize fitness. We are also adding the difference term to make sure that we do not overfit our algorithm on either training or validation dataset.

Crossover function

We have implemented a custom crossover function. The basic idea it to use uniform crossover for n vectors, where n is randomly chosen. The process is:

n	Probability
2	35%
3	45%
4	20%

We have done this since we believe that 2 vectors may leave out some information, 3 vectors contains enough information. and 4 vectors may contain additional unnecessary information.

Suppose we select n vectors and label them in alphabetical order starting from a in decreasing order of fitness. Let our final vector be x, then we have defined x to be:

For n = 2, x_i =
$a_i, 60\%$
$b_i, 40\%$

For n = 3, x_i =
$a_i, 50\%$
$b_i, 30\%$
$c_i, 20\%$

For n = 4, x_i =
$a_i, 45\%$
$b_i, 25\%$
$c_i, 15\%$
$d_i, 15\%$

Note: *For n = 4, we decided to keep the probability for vectors c and d equal since they probably won't differ much in fitness, but still can help in randomization.*

Mutations

We mutate our vector(x) using the following algorithm:

```
For each dimension in x:
- Choose to mutate this dimension with probability MUTATION_PROB
    - If chosen to mutate, check if the weight of current dimension is 0:
        - If weight of current dimension if 0, assign a random value between the given range of weights.
        - If weight of current dimension is not 0, then add a random value between -VAR_PERCENTAGE of $x_i$ and VAR_PERCENTAGE of $x_i$
        - Continue to next dimension

- If chosen not to mutate, continue to next dimension
```

Hyperparameters

POPULATION_SIZE = 10, number of vectors per generation

GENERATIONS = 9, Number of generations to create

MATING_POOL_SIZE = 10, number of vectors considered during crossover vector selection

MIN = -10, Minimum weight of a dimension

MAX = 10, Maximum weight of a dimension

MUTATION_PROB = 0.7. Probability that a dimension will be chosen for mutation

VAR_PERCENTAGE = 25, max percentage that can be added or subtracted from the dimension during mutation

ORIGINAL_ERROR = 381807315968.0, original overfit vector's sum of training set error and validation set error

BEST_PARENTS = 3, number of parents which will be passed on to next generation

TRAIN_FACTOR = 0.95, multiplied to the training error to increase or decrease its contribution to the fitness value

TEST_FACTOR = 1.0, multiplied to the validation error to increase or decrease its contribution to the fitness value

DIFF_FACTOR = 1.0, multiplied to the absolute difference of validation error and test error to increase or decrease its contribution to the fitness value

MIN_MUTATE = 100, minimum number of times we mutate a vector while creating the initial population from the overfit vector

MAX_MUTATE = 1000, maximum number of times we mutate a vector while creating the initial population from the overfit vector

Statistics

Iteration Needed to converge

Starting from the overfit vector, the code took approximately **100** generations for the training set MSE to overtake the validation set MSE.
But, the fitness function used for these generations did not consider the difference between the errors.
It then took approximately **2000** generations to converge to the final vector.

Number of Restarts

We restarted training vector **3** times.

1. When we switched from making a completely randomised population, to filling the population with mutated vectors of the overfit vector.
2. When we realised that our *mutate* function was incorrect. (We were replacing given weight with a random value in the given range for weights.)
3. When we added a mating pool, and stored previous code run's final generation population and their errors.

For the changes made after these, we retained the generation and created branches of generations, in a way that we could revert back to a population of a generation we know is best. This data is stored in the file named *population.txt*.

Heuristics used

1) Directional mutation (failed):
Tried to use the best vectors of a population to add a bit of bias to mutations that increase the fitness but we could not determine whether it was helpful or not and all vectors started to converge too rapidly.

2) Binary crossover (failed):
Tried using binary crossover but the performance decreased when using it.

3) Mutate (failed):
For weight of each dimension of the vector, replace it by a random value in the given range for weights.

4) Singlepoint crossover (partial success):
Used single point crossover in the beginning but it stopped giving better vectors after a certain amount of time. Replaced with Hybrid Crossover

5) Hybrid crossover (partial success):
This was our intermediate solution in which we used single point crossover with probability 60% and uniform crossover with probability 40%. Replaced this with our selection crossover

6) Elitism (Used):
We are using elitism while forming the new generation

7) Population creation (Used):
We are mutating the initial overfit vector POPULATION_SIZE - 1 times to create our initial population if not given.

8) selection crossover (Used):
Explained in the crossover section

Train and Validation error

S. No.	Vector	Training set MSE	Validation set MSE
1.	[1.0796526941030586, -8.715162711943131e-19, 3.871354440528529e-06, 1.7653154651736457e-09, -1.2486049836655162, 2.1471529604497616e-18, 5.094795413663314e-21, 2.4044189773090542e-14, 1.0558133124332984e-07, -9.757122653416584e-16, -1.444904845379374e-14]	85789478076.08893	85860947393.53752
2.	[0.7418155574643469, -3.4450243325386273e-18, 3.2261440074855244e-06, 3.175351759871859e-09, -1.2486049836655162, 7.17799837783098e-19, 5.0167540463567284e-21, 2.483229218868748e-14, 1.056441508086754e-07, -1.8213786816009663e-15, -1.0019745817707677e-14]	85952768142.60727	86005658803.69467
3.	[1.847052262841336, -2.5068768507801048e-18, 4.659740503058584e-06, 2.2800933816946775e-09, -1.2486049836655162, 3.9945130632584965e-19, 6.535555699401268e-21, 2.5784437558132038e-14, 1.056441508086754e-07, -3.0391827416463197e-15, -7.38011537222921e-15]	86008133144.05466	86023162332.26974
4.	[2.0780107356915596, -3.992838840428164e-18, 4.516809843168537e-06, 2.8002915027458477e-09, -1.2486049836655162, 2.8818471692097994e-19, 8.129227218592027e-21, 5.215097700409277e-14, 1.056441508086754e-07, -3.300387853578753e-15, -4.8213371071931044e-15]	86018693956.65129	86034879036.24663
5.	[2.388702449057477, -4.428532357378065e-18, 3.719949358824128e-06, 2.7070450375210467e-09, -1.2486049836655162, 1.712455798799604e-19, 7.808053560215505e-21, 5.0302136123933467e-14, 1.056441508086754e-07, -1.9898530793314443e-15, -3.9842623013157476e-15]	86039524180.61018	86040999679.32416
6.	[2.6818812113350003, -4.314964270135856e-18, 4.057299232887971e-06, 6.826389375060461e-09, -1.2486049836655162, 1.5553402114948158e-19, 1.3314811505159597e-20, 6.85844393372265e-14, 1.056441508086754e-07, -3.2542763496813605e-15, -2.7153269412270014e-15]	86036286133.70601	86045633451.5842
7.	[10.0, -9.150504594076882e-18, 5.0533594624717434e-06, 9.84543056488233e-10, -1.2486049836655162, 4.3576463454620555e-20, 8.53887837444912e-21, 1.128015450719615e-13, 1.0563239599063873e-07, -7.908235682492684e-15, -4.671789492731e-15]	86094693232.60085	86024187443.89883

8.	[6.721321544621738, -1.1877921234621972e-17, 6.8904241546123365e-06, 5.7470406913645966e-09, -1.2486049836655162, 4.4656815455991816e-20, 4.025632784891203e-21, 1.4104150950287807e-13, 1.0563239599063873e-07, -8.756274436367583e-15, -8.692630883341574e-15]	86116468204.83037	86010770562.37679
9.	[6.8844350902206175, -9.794730566767862e-18, 1.828988602880485e-05, 4.855622630975936e-09, -1.2486049836655162, 1.834386010950058e-20, 4.35552545923755e-21, 1.2062971267624513e-13, 1.0574888606925636e-07, -1.5686936339548276e-14, -1.3673296891880275e-14]	85918806169.71979	86163120117.01878
10.	[4.184070668290893, -7.850456642755217e-18, 2.6623847537377427e-05, 5.036305913703038e-09, -1.2582264023072198, 1.9616216160068823e-20, 3.7313992965337805e-21, 4.931505123879456e-13, 1.0664583512488755e-07, -8.623342104104946e-15, -1.2760055435313701e-14]	86220260976.6219	86231590827.8452

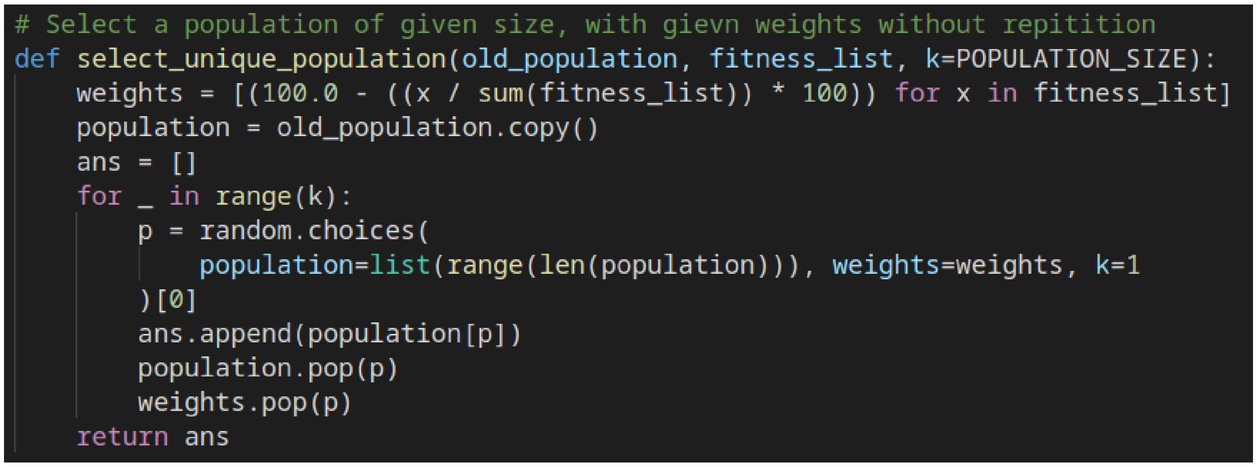
After beginning from the training set MSE and validation set MSE of the overfit vector, *(13510723202.57021, 368296581138.17303)*, the vectors generated by our algorithm are better in the following ways:

- The training set MSE is larger than that of overfit vector, which indicates that the new vector is no longer overfit on the training set.
- The validation set MSE is less than that of overfit vector, which indicates that the new vector performs better than the overfit vector on a data set other than the one it was trained on.
- The difference between training set MSE and validation set MSE is much less than that of overfit vector, which indicates that the new vector is standardised on both, training set and validation set, and that it has a good chance to do well on an unseen data set.

Miscellaneous tricks

Select Unique Vectors

While choosing vectors for crossover, we are making sure to select unique vectors using weighted probability.



```
# Select a population of given size, with gievn weights without repitition
def select_unique_population(old_population, fitness_list, k=POPULATION_SIZE):
    weights = [(100.0 - ((x / sum(fitness_list)) * 100)) for x in fitness_list]
    population = old_population.copy()
    ans = []
    for _ in range(k):
        p = random.choices(
            population=list(range(len(population))), weights=weights, k=1
        )[0]
        ans.append(population[p])
        population.pop(p)
        weights.pop(p)
    return ans
```

Figure 3: Function in the code to select k unique vectors from a given population with weighted probability