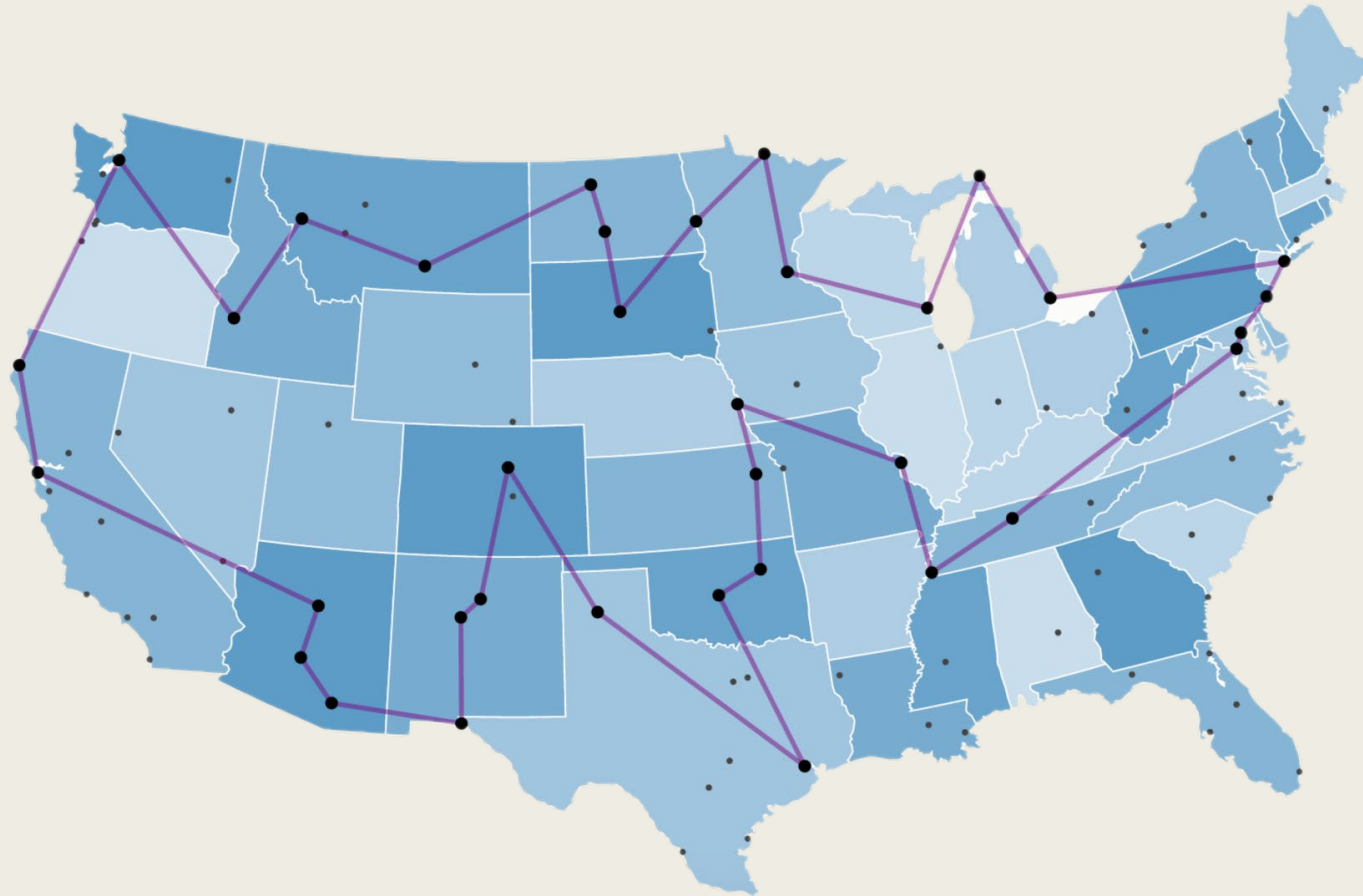


AN HYBRID METAHEURISTIC APPROACH TO THE TRAVELING SALESMAN PROBLEM

INTRODUCTION

Travelling Salesman Problem



TSP

is an algorithmic problem tasked with finding the shortest route between a set of points and locations that must be visited

DATASETS

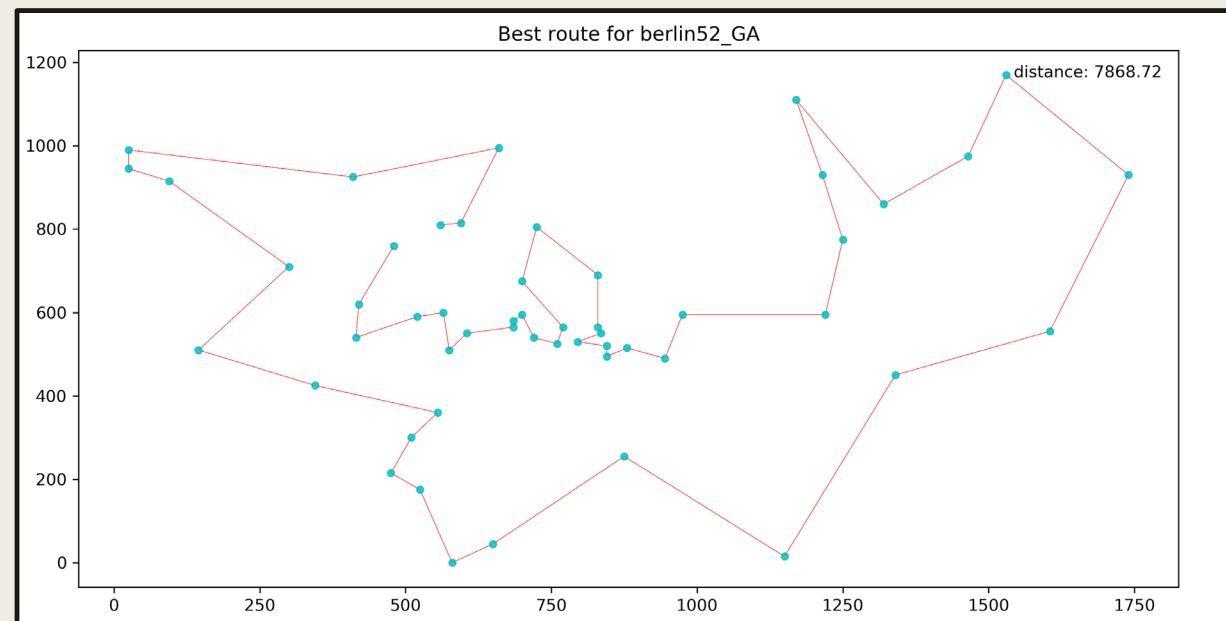
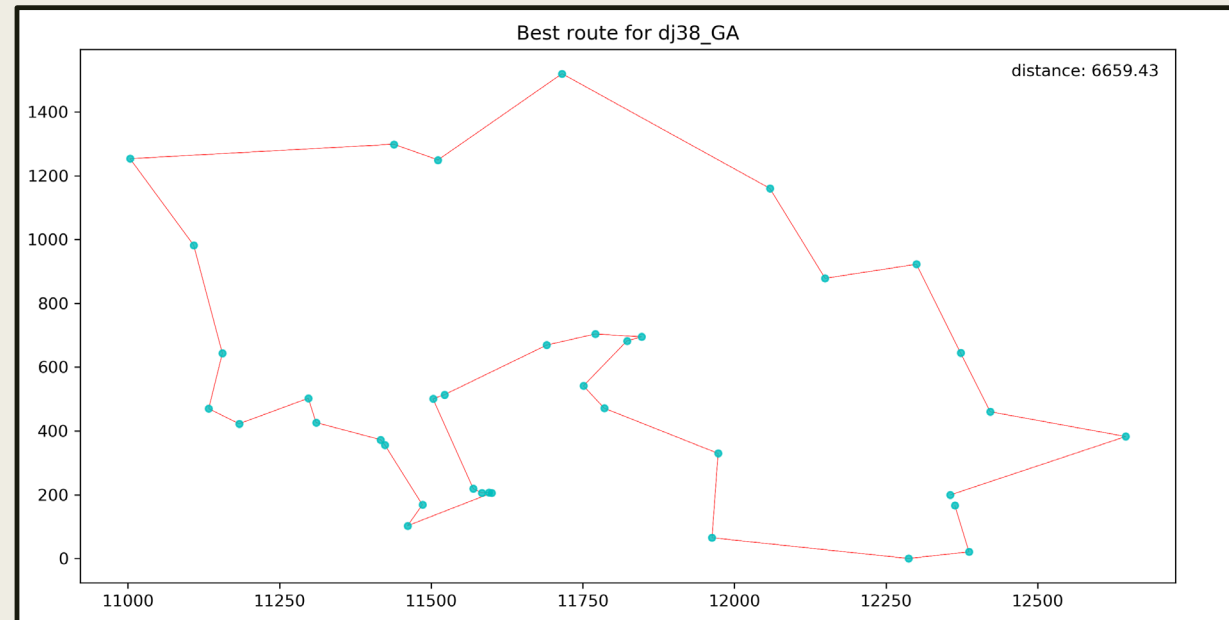
■ dj38

■ berlin52

■ ch130

■ d198

■ pr1002



METHODOLOGICAL APPROACH

ACO – Ant-Q – GA – KGA

ANT FAMILY ALGORITHMS

- inspiration from biology
- accomplish difficult tasks exploiting collaboration
- pheromone as a communication channel
- the more ants follow a specific path,
the more likely it becomes to be followed
- shortest path problems



Ant Colony Optimization

- multi-agent collaborative approach
- pheromone evaporation and deposit
 - exploration vs exploitation tradeoff

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \Delta\tau_{ij}$$

- artificial ants might have different aims
 - pheromone guided moves vs heuristically driven ones

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta} \quad \text{if } j \in N_i^k$$



RULE 1.

The ant must visit each point exactly once.

RULE 2.

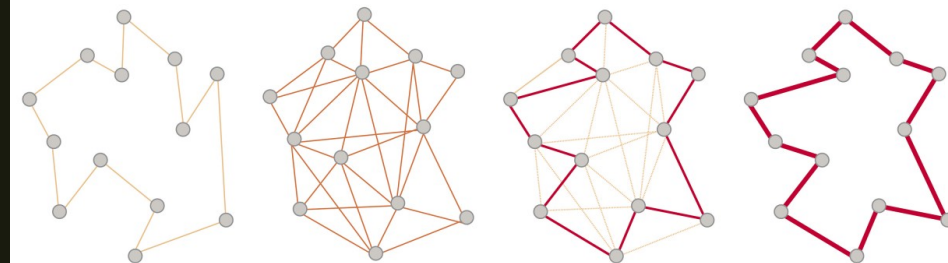
A distant point has less chance of being chosen.

RULE 3.

The more intense the pheromone trail laid out on the path between two points, the greater the probability that the path will be chosen.

RULE 4.

The ant deposits pheromones on all paths it traverses. After each iteration, trails of pheromones evaporate, reinforcing the preferred path.



Dorigo, Gambardella, Ant Colony System:
A Cooperative Learning Approach to the Travelling Salesman Problem.
In: IEEE Transactions on Evolutionary Computation, Vol.1 No.1, pp.53-66

Ant-Q

a reinforcement learning approach

main idea

- integrate a Q-learning-like rule in the pheromone update procedure

$$\tau_{ij} = (1 - \alpha)\tau_{ij} + \alpha(\Delta\tau_{ij} + \gamma \max_{l \in N_j^k} \tau_{jl})$$

- and in the single decision process

$$s = \begin{cases} \arg \max_{a \in J_k(s)} [Q(s, a)]^\alpha [\eta(s, a)]^\beta & \text{if } q \leq q_0 \\ S & \text{otherwise} \end{cases}$$

Parallel Implementation Hints



- ACO algorithm are quite memory expensive, but... naturally parallelizable!
- parallel systems (parent/children)
 - running on each core
- local pheromone matrices
- global updates every iteration (parent)
 - providing each child with an updated mean pheromone matrix
- technically
 - Open MPI (<https://www.open-mpi.org>)
 - mpi4py (<https://mpi4py.readthedocs.io/en/stable>)

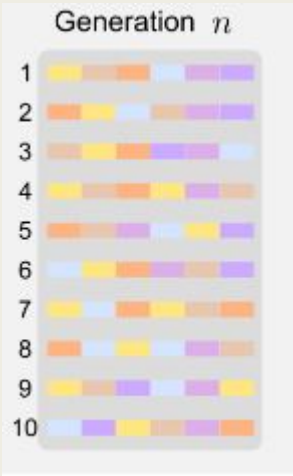
GENETIC ALGORITHM

- based on a biological metaphor (*Darwinism*)
- individuals as chromosomes (*genotypes*) into a population
- Individuals' features as phenotypes
- crossover operator as gene transfer
- random mutation at each generation

Genetic Algorithm

generate population

(chromosomes)



mutation

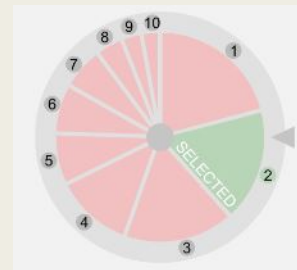


selection mechanism

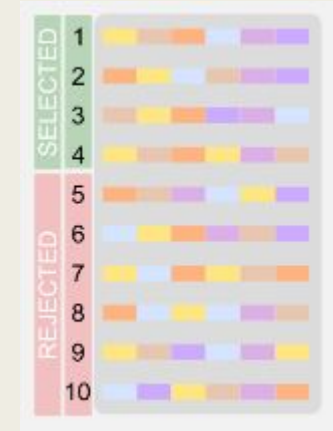
tournament selection



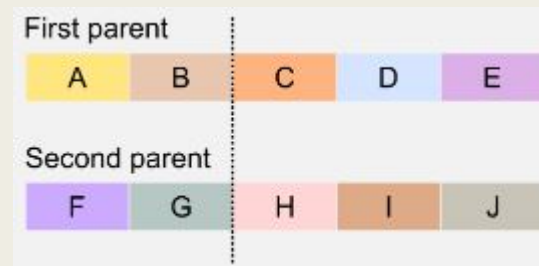
roulette-wheel selection



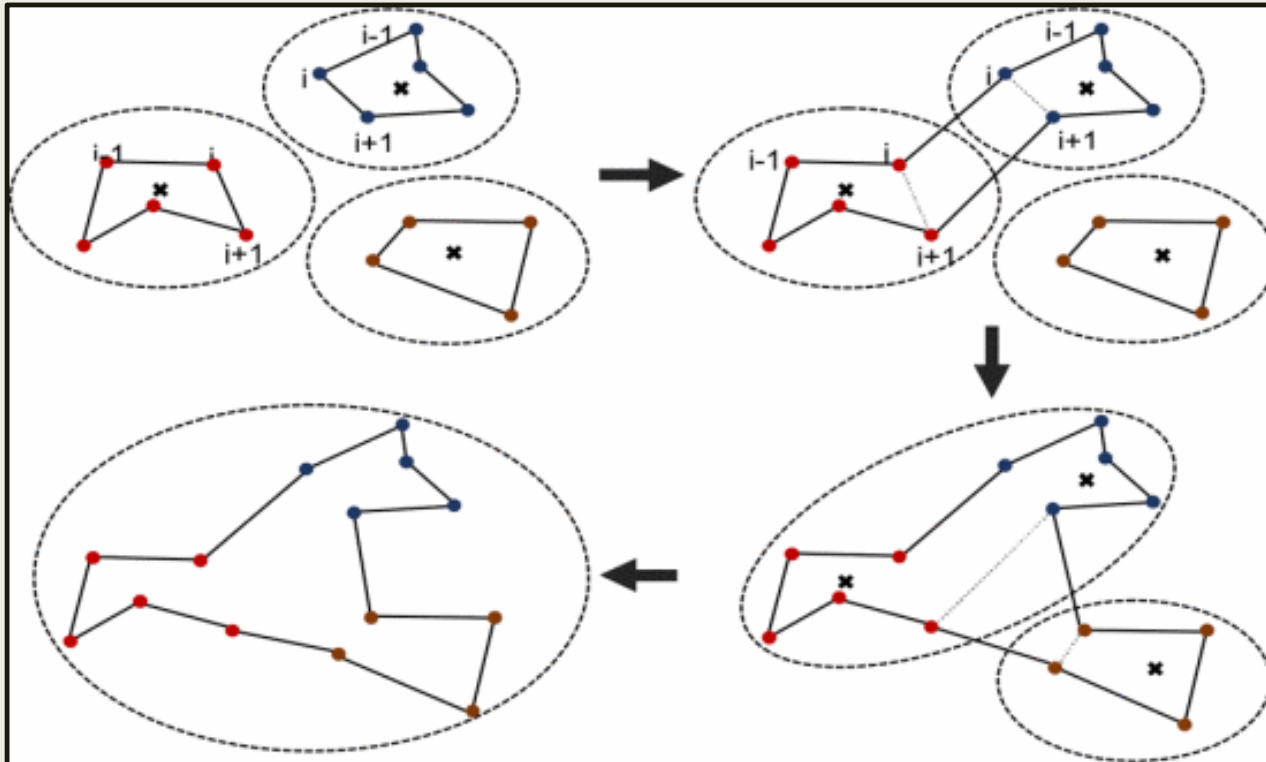
evaluation and elitism



crossover (single-point)



K-means Genetic Algorithm

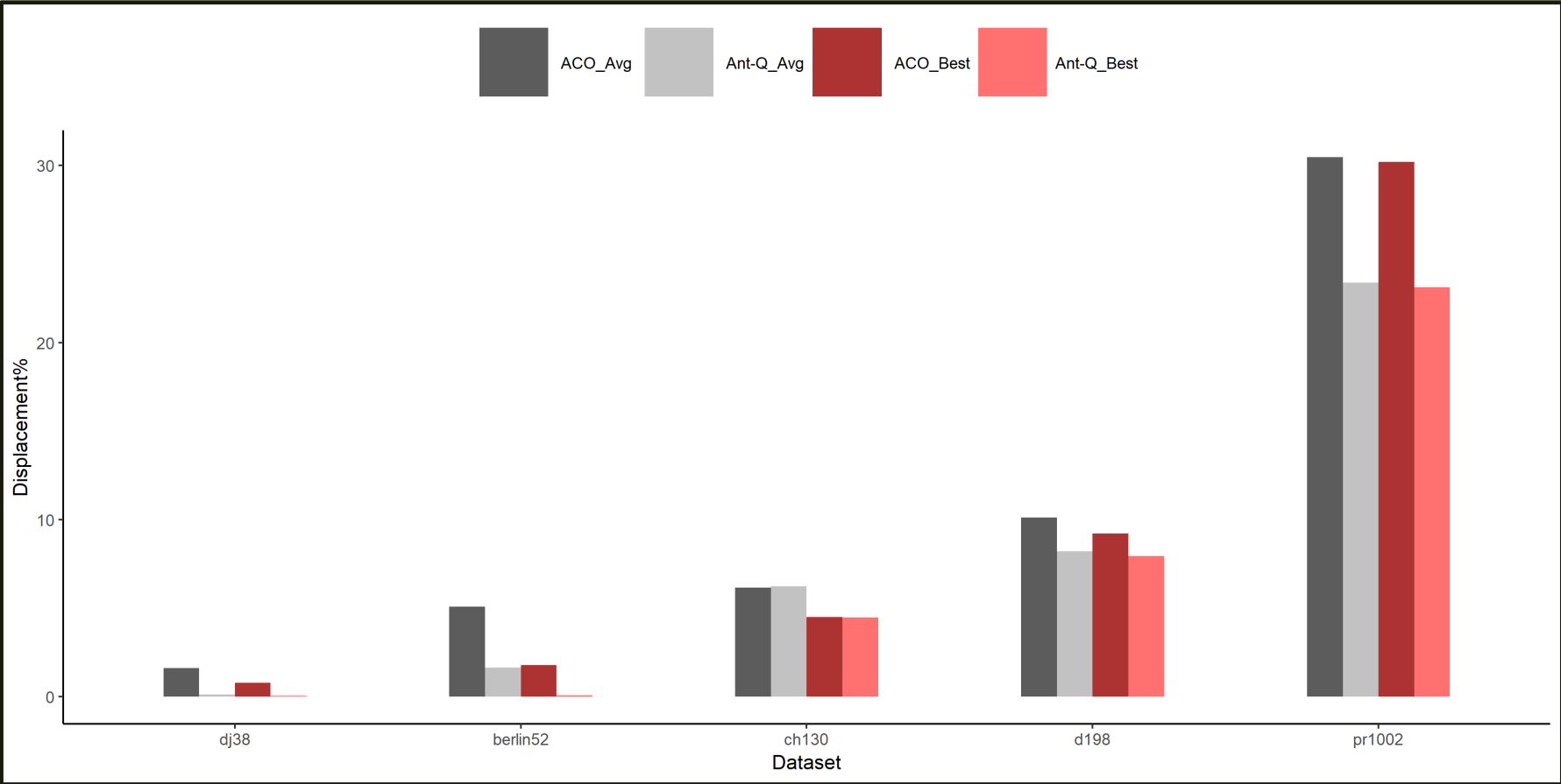


- hybrid implementation of GA
- transform wide problem into smaller sub-problems (*clusters*)
- solve sub-problems with GA
- reconstruct optimal solution from sub-problems solutions



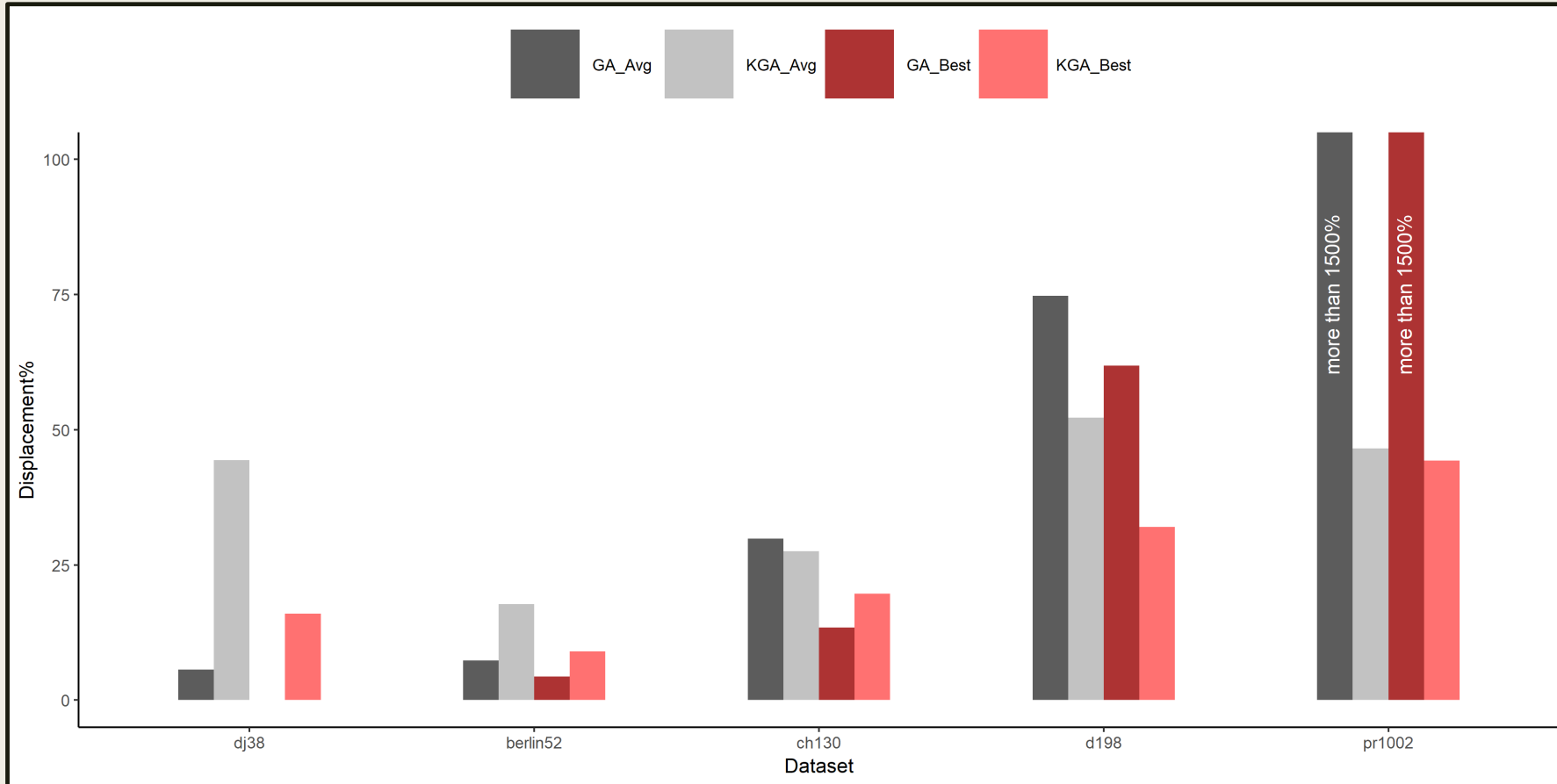
RESULTS

ACO – ANT-Q



Dataset	ACO							Dataset	Ant-Q						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)		OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38 (1000 it)	6656	6763.03	75.16	6708.04	1.61	0.78	75	dj38 (1000 it)	6656	6663.99	4.16	6659.43	0.12	0.05	37
berlin52 (1000 it)	7542	7925.39	162.00	7677.66	5.08	1.80	320	berlin52 (1000 it)	7542	7666.17	113.87	7548.99	1.65	0.09	170
ch130 (500 it)	6110	6487.19	74.20	6385.46	6.17	4.51	9240	ch130 (500 it)	6110	6491.31	70.01	6383.42	6.24	4.47	8400
d198 (100 it)	15780	17376.23	105.81	17235.44	10.12	9.22	6540	d198 (100 it)	15780	17075.81	39.69	17032.75	8.21	7.94	2880
pr1002 (10 it)	259054	337976.61	833.96	337309.96	30.47	30.21	6180	pr1002 (10 it)	259054	319646.49	1009.39	318960.00	23.39	23.12	6120

GA – KGA



Dataset	GA						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38	6656	7032.91	574.34	6659.43	5.66	0.05	263
berlin52	7542	8095.35	167.27	7868.72	7.34	4.33	286
ch130	6110	7933.02	1041.27	6929.81	29.84	13.42	435
d198	15780	27579.73	1869.54	25537.85	74.78	61.84	604
pr1002	259045	4666413.09	12608.57	4652556.08	1701.39	1696.04	2641

Dataset	KGA						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38	6656	9608.77	1817.02	7720.03	44.36	15.99	140
berlin52	7542	8879.59	446.69	8218.95	17.74	8.98	188
ch130	6110	7790.85	312.17	7314.08	27.51	19.71	409
d198	15780	24023.86	3066.94	20830.94	52.24	32.01	1413
pr1002	259045	379495.87	6343.57	373865.26	46.50	44.32	4456

CONCLUSIONS

KEY POINTS



EFFECTIVE IMPROVEMENT OF THE
HYBRIDIZED APPROACH WITH
RESPECT TO THE CLASSIC VERSION
OF EACH ALGORITHM



ANT FAMILY – BEST PERFORMANCES
ON SMALL/MEDIUM SIZED PROBLEMS



KGA – MORE PERFROMANT
ON LARGE DATASETS



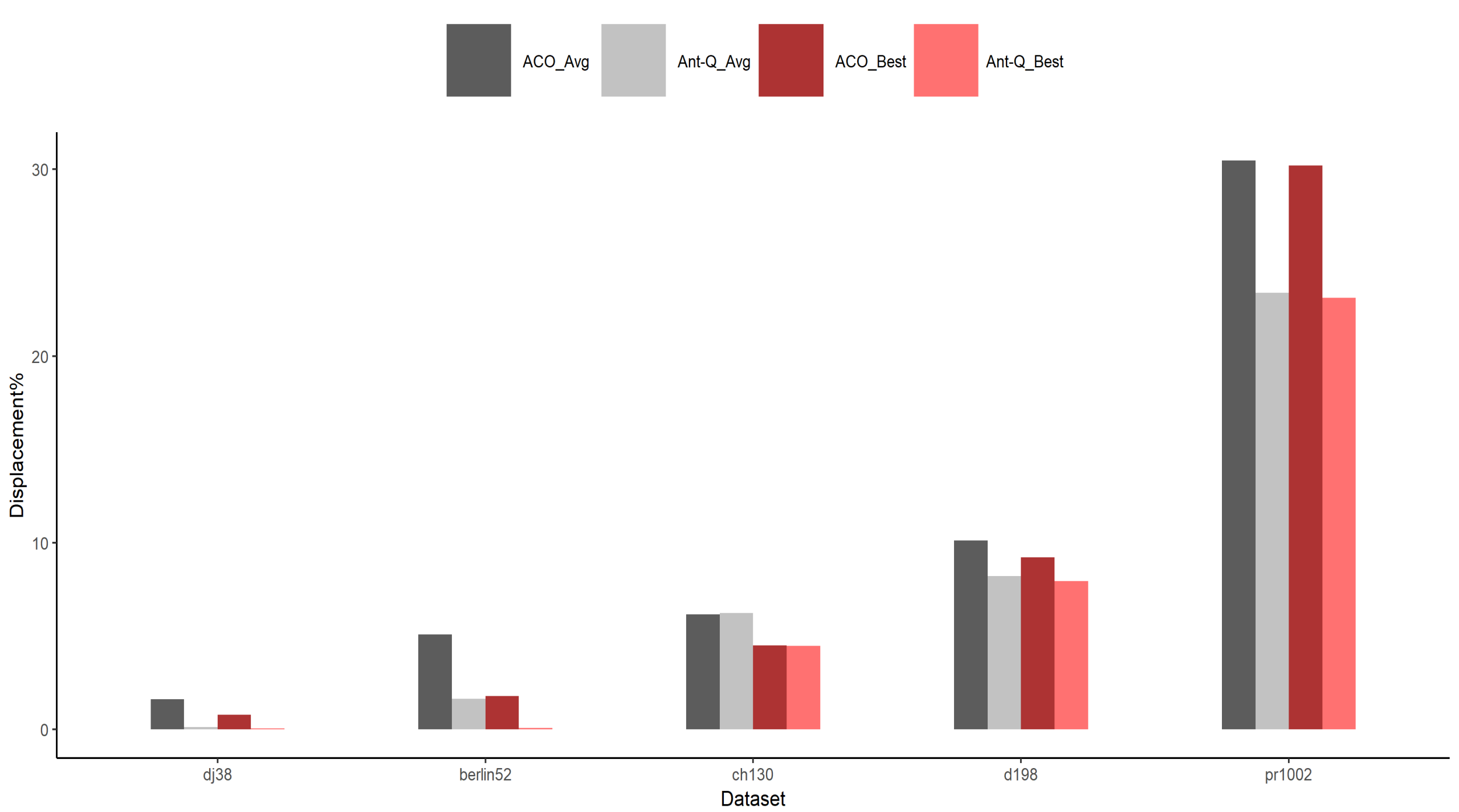
ACO AND ANT-Q SLOWER ON HIGHER
DIMENSIONS BUT FIND BETTER
SOLUTIONS THAN EA

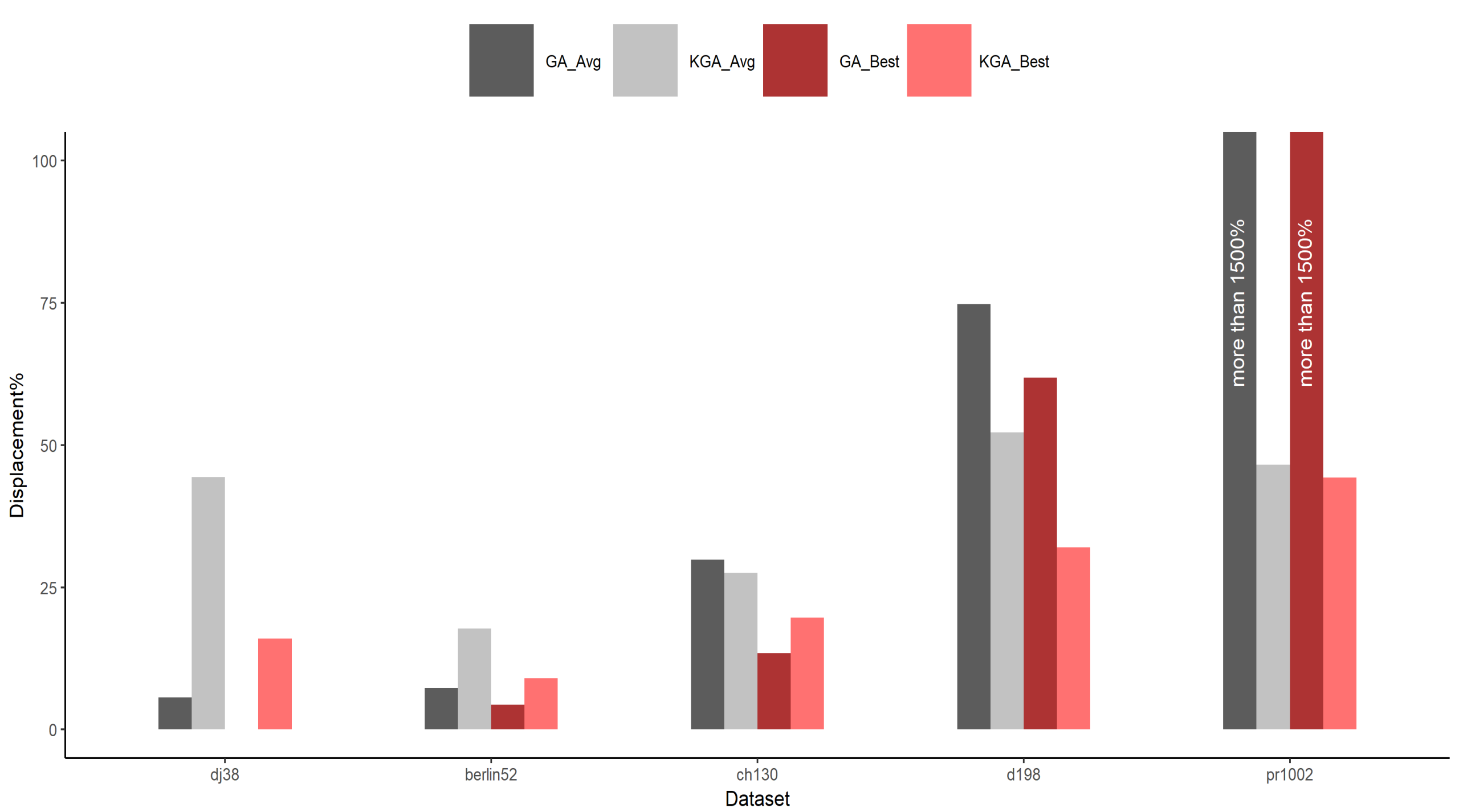
FUTURE WORK

it could be interesting to further combine
Ant-Q and KGA

TANK YOU







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pr1002 (10 it)	259054	337976.61	833.96	337309.96	30.47	30.21	6180

Dataset	Ant-Q						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38 (1000 it)	6656	6663.99	4.16	6659.43	0.12	0.05	37
berlin52 (1000 it)	7542	7666.17	113.87	7548.99	1.65	0.09	170
ch130 (500 it)	6110	6491.31	70.01	6383.42	6.24	4.47	8400
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Algorithm Ant Colony Optimization

Main Algorithm

```
0: initialize best_dist and best_path to None
1: for generation in generations:
2:   create n_ants artificial ants
3:   for one_ant in ants:
4:     make a single ant path (see Make path)
5:     compute the path length
6:     update best_dist and best_path
7:   update the pheromone matrix
   (local update only for child processes, according to Eq. (10))
8:   every a certain n of iterations:
9:     update the global pheromone matrix
   (shared in MPI environment among master&child.)
10: return best_dist, best_sol
```

Make path

```
1: start from a vertex
2: add start vertex to visited nodes
3: for each remaining vertex:
4:   list the neighbours
5:   list the not yet visited neighb
6:   calculate the probability of choosing a vertex (according to Eq. (7))
7:   choose the vertex according to probability
8:   add the chosen vertex to the visited list
9:   return the chosen vertex id
```

Local update pheromone matrix

```
1: for ant in ant_colony :
2:   for each vertex of one_ant_path :
3:     increase pheromone_matrix between current and next vertex of  $\Delta\tau$ 
   (according to Eq. (10))
```

Global update pheromone matrix (parallelism)

```
1: gather from MPI env all the pheromone matrices
2: if process is the parent process (rank==0):
3:   for each element average over the n_cores matrices.
4: broadcast obtained pheromone matrix to the other
   processes
```

Algorithm Ant-Q algorithm

Main Algorithm

```
0: initialize best_dist and best_path to None
1: for generation in generations:
2:   create n_ants artificial ants
3:   for each ant:
4:     make a single ant path (see Make path)
5:     compute the path length
6:     update best_dist and best_path
7:     update pheromone matrix with delayed rewards
   (according to Eq. (14))
8:   update the global pheromone matrix
   (shared in MPI environment among master&child.)
9: return best_dist, best_sol
```

Make path

```
1: start from a vertex
2: add start vertex to visited nodes
3: for each remaining vertex:
4:   list the neighbours
5:   list the not yet visited neighb
6:   generate a random number  $q \in \{0, 1\}$ 
7:   if  $q < q_0$ : (threshold)
8:     select next vertex according to Eq. (12)
9:   else:
10:    calculate the probability of choosing a vertex
11:    (according to Eq. (7))
12:    choose the vertex according to probability
13:    add the chosen vertex to the visited list
14:    give local rewards (local update pheromone matrix)
15:    return the chosen vertex id
```

Local update pheromone matrix

```
1: for ant in ant_colony :
2:   for each vertex of one_ant_path :
3:     increase pheromone_matrix between current
   and next vertex of a  $\Delta\tau$  (according to Eq. (11))
```

Global update pheromone matrix (parallelism)

```
1: gather from MPI env all the pheromone matrices
2: if process is the parent process (rank==0):
3:   for each element average over the n_cores matrices.
4: broadcast obtained pheromone matrix to the other
   processes
```

Algorithm Genetic Algorithm

```
1: procedure Genetic( $T_m$ ,  $T_p$ , elite_n, Selection, MaxGen)
2:    $Pop \leftarrow GeneratePopulation(T_p)$ 
3:    $Pop \leftarrow Evaluation(Pop)$ 
4:   for  $i = 1 \dots MaxGen$  do
5:      $Pop \leftarrow Selection(elite\_n \text{ from } Pop)$ 
6:      $Pop \leftarrow Crossover(Pop)$ 
7:      $Pop \leftarrow Selection(Pop)$ 
8:     With probability  $T_m$  do:
11:       $Pop \leftarrow Mutation(Pop)$ 
12:   end for
13:   return the best solution in  $Pop$ 
14: end procedure
```

Algorithm K-Means Algorithm

```
1: Set the  $K$  cluster centers randomly;
2: repeat
3:   for each vertex do
4:     Calculate distance measure to each cluster;
5:     Assign it to the closest cluster;
6:   end
7:   recompute the cluster centers positions;
8: until stop criteria are met;
```

Algorithm KGA

```
1: input an TSP;
2: K-Means is adopted to cluster the TSP into  $k$  sub-problems
3: For each sub-prob  $i = 1$  to  $k$ , do:
4:   repeat
5:     GA procedure
6:   until stop criteria are met
7:   Output shortest path for sub-problem  $i$ ;
8: End
9: Seek for the best combining seq  $S$  with GA
10: Combine all those shortest path into one tour
11: Output the shortest whole travelling tour.
```
