```
from ce.algorithms.greedy_heuristics import random_solution
       from ce.algorithms.local_search import multiple_start_local_search, large_scale_search, two_edges_neighborhood
       from ce.tsp import create_tsp, TSP
       from ce.utils.experiments import experiment, quality_plots
       Large scale neighborhood search
       Nina Zukowska 148278, Antoni Solarski 148270
In [2]: problem_instance_A_path = '../../data/TSPA.csv'
       problem_instance_B_path = '../../data/TSPB.csv'
       problem_instance_C_path = '../../data/TSPC.csv'
       problem_instance_D_path = '../../data/TSPD.csv'
In [3]: tspa = create_tsp(problem_instance_A_path)
       tspb = create_tsp(problem_instance_B_path)
       tspc = create_tsp(problem_instance_C_path)
       tspd = create_tsp(problem_instance_D_path)
       Algorithms
       Break: simply remove 30% of nodes (consecutive).
       Repair: use a weighted regret (with k = 0.5) greedy cycle.
       def break_solution(solution: List[int], break_factor=0.3):
          break_length = int(break_factor * len(solution))
          start_index = np.random.randint(1, len(solution) - break_length)
          end_index = start_index + break_length
           return solution[:start_index] + solution[end_index:]
       def repair_solution(solution: List[int], tsp: TSP):
          while len(solution) < tsp.get_desired_solution_length():</pre>
              solution = extend_cycle(solution, tsp, 0.5)
          return solution
       def large_scale_search(tsp: TSP, init_solution: List[int], time_limit: float, neighborhood_fn, with_ls: bool):
          best_solution, _ = steepest_local_search_cache(tsp, init_solution, neighborhood_fn)
          best_solution_cost, iterations = tsp.get_solution_cost(best_solution), 0
          start_time = time.time()
          while time.time() - start_time < time_limit:</pre>
              iterations += 1
              new_solution = break_solution(best_solution)
              new_solution = repair_solution(new_solution, tsp)
              if with_ls:
                  new_solution, _ = steepest_local_search_cache(tsp, new_solution, neighborhood_fn)
              new_solution_cost = tsp.get_solution_cost(new_solution)
              if new_solution_cost < best_solution_cost:</pre>
                 best_solution = new_solution
                 best_solution_cost = new_solution_cost
           return best_solution, iterations
       Experiments
In [4]: n_runs = 20
       time_limit = 90.0
       experiment_names = ["large scale (without ls)", "large scale (with ls)"]
       previous_experiments = ["multiple start local search", "iterated local search"]
       def without_ls_experiment_provider(tsp: TSP, random_inits, time_limit):
          return lambda x: large_scale_search(tsp, random_inits[x], time_limit, two_edges_neighborhood, False)
       def with_ls_experiment_provider(tsp: TSP, random_inits, time_limit):
          return lambda x: large_scale_search(tsp, random_inits[x], time_limit, two_edges_neighborhood, True)
       Instance C
In [5]: random.seed(13)
       np.random.seed(13)
       random_inits_c = [random_solution(tspc) for i in range(n_runs)]
       Large scale search without local search
In [6]: %%time
       random.seed(13)
       np.random.seed(13)
       *************************************
      cost: 48488.7, (47855 - 50241) |
                                     iter: 602.0, (476 - 627)
                                                               | time: 90.6s, (90.5s - 91.5s)
      *************************
      CPU times: total: 30min 14s
      Wall time: 30min 12s
```

In [8]: results\_list\_c, best\_solutions\_c = [without\_ls\_costs\_c, with\_ls\_costs\_c], [without\_ls\_best\_solution\_c, with\_ls\_best\_solution\_c]

In [9]: with open('../report\_6/results\_c.json', 'r', encoding='utf-8') as f:
 previous\_results\_list\_c = json.load(f)
with open('../report\_6/best\_solutions\_c.json', 'r', encoding='utf-8') as f:
 previous\_best\_solutions\_c = json.load(f)

Categorical Scatter Plot

| The proof of the

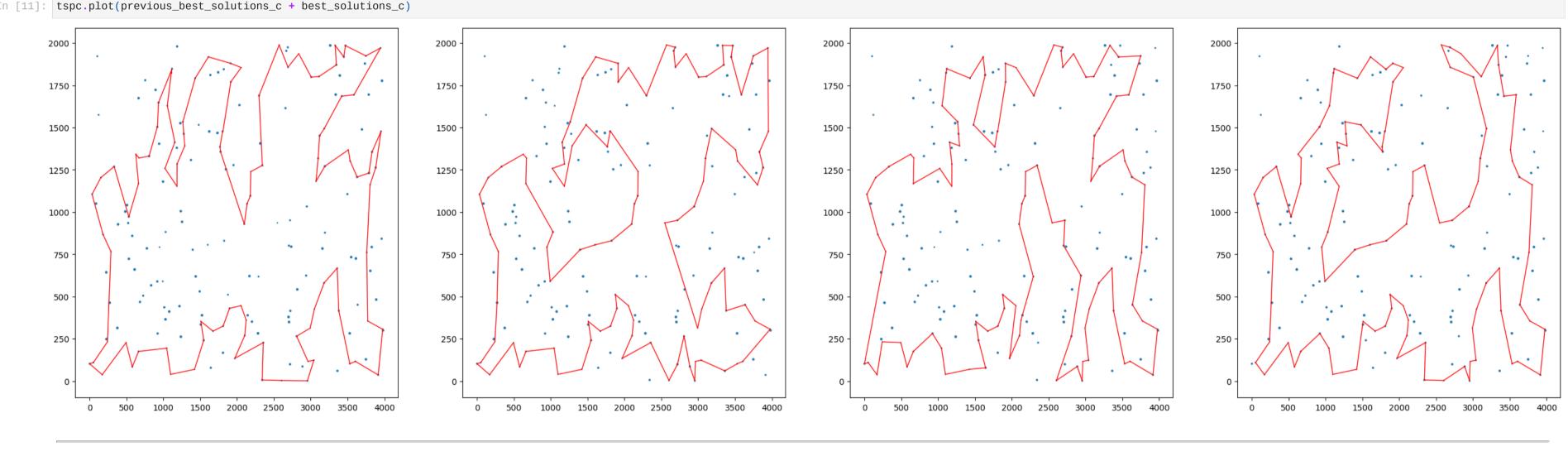
48500
48500
47500
multiple start local search iterated local search Algorithm

tspc.plot(previous\_best\_solutions\_c + best\_solutions\_c)

2000
2000
2000

\*

cost: 48181.8, (47259 - 49730) | iter: 533.5, (520 - 542) | time: 90.6s, (90.4s - 90.7s)



## In [12]: random.seed(13) np.random.seed(13) random\_inits\_d = [random\_solution(tspd) for i in range(n\_runs)]

Instance D

In [1]: import json

import random
import sys

import numpy as np

sys.path.insert(1, '../../src')

## 

Large scale search with local search

In [7]: **%%time** 

random.seed(13)
np.random.seed(13)

CPU times: total: 30min 11s

Wall time: 30min 11s

Wall time: 30min 11s

Large scale search with local search

In [14]: %%time random.seed(13)

## 

previous\_best\_solutions\_d = json.load(f)

CPU times: total: 30min 11s

CPU times: total: 30min 11s

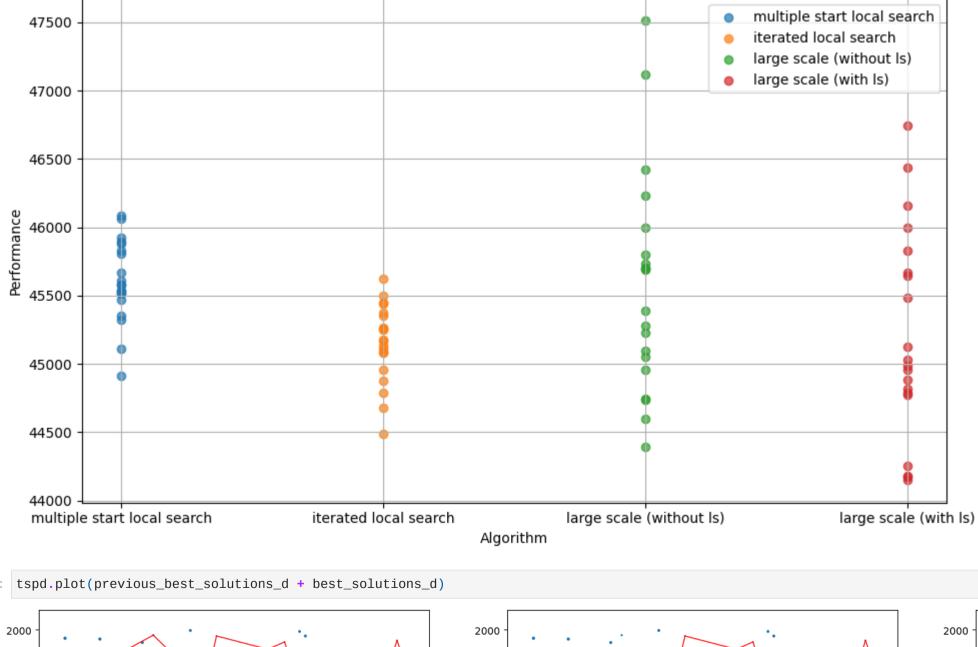
Wall time: 30min 11s
In [15]: results\_list\_d, best\_solutions\_d = [without\_ls\_costs\_d, with\_ls\_costs\_d], [without\_ls\_best\_solution\_d, with\_ls\_best\_solution\_d]

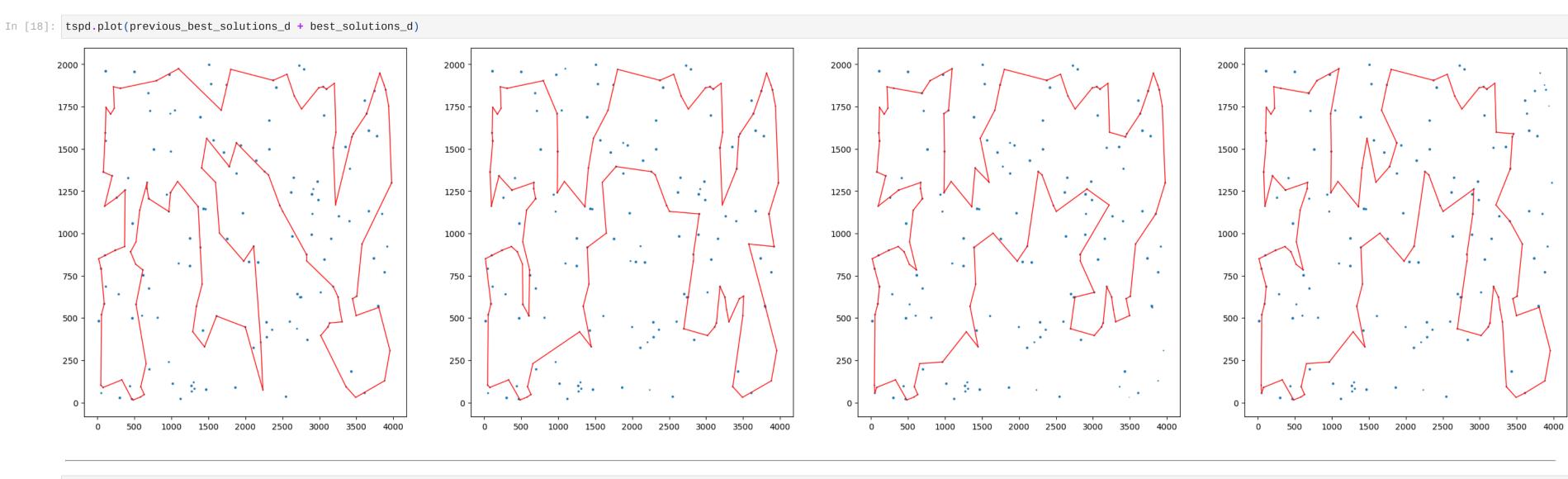
In [16]: with open('../report\_6/results\_d.json', 'r', encoding='utf-8') as f:
 previous\_results\_list\_d = json.load(f)

Categorical Scatter Plot

In [17]: quality\_plots(previous\_results\_list\_d + results\_list\_d, categories=previous\_experiments + experiment\_names)

with open('../report\_6/best\_solutions\_d.json', 'r', encoding='utf-8') as f:





with open('best\_solutions\_c.json', 'w', encoding='utf-8') as f:
 json.dump(best\_solutions\_c, f, ensure\_ascii=False, indent=4)

In [20]: with open('results\_d.json', 'w', encoding='utf-8') as f:
 json.dump(results\_list\_d, f, ensure\_ascii=False, indent=4)
with open('best\_solutions\_d.json', 'w', encoding='utf-8') as f:
 json.dump(best\_solutions\_d, f, ensure\_ascii=False, indent=4)

## Conclusions

The large-scale search results were more diverse compared to multiple start local search and iterated local search from the last report. However, on average (and considering the best solutions found) large-scale search outperformed MSLS and ILS, especially with local search. This is expected, as local search usage improved the solution found with heuristic (nearest-neighbor heuristic).

The nearest-neighbor heuristic was chosen because of its much smaller time complexity than greedy cycle one, thanks to that large-scale search was able to perform much more "loops" than with the usage of greedy-cycle (in our experiments local search was performing more than 600 iterations without local search and more than 500 with Is not too few - in comparison to 800 iterations done by MSLS).