

第一问：基于Branch and cut求解的TSP/Pickup and delivery Problem

$$\begin{aligned} \min & d + \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ijk} \\ \text{s. t. } & \begin{cases} d = \max_{k \in K} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ijk} \\ \sum_{j \in V} \sum_{k \in K} x_{ijk} = 1, \forall i \in V - \{0\} \\ \sum_{j \in V} x_{ijk} - \sum_{j \in V} x_{jik} = 0, \forall i \in V, k \in K \\ \sum_{j \in V} x_{0jk} = 1, \forall k \in K \\ \sum_{i \in S} \sum_{j \in S} x_{ijk} \leq |S| - 1, \forall S \subset V - \{0\}, S \neq \emptyset, k \in K \\ x_{iik} = 0, \forall i \in V, k \in K \\ x_{ijk} \in \{0, 1\} \end{cases} \end{aligned}$$

在处理TSP问题中的子环问题时，常用的方法有基于Branch and bound的Branch and cut算法、基于Column Generation的Branch and Price算法和Lagrange Relaxation算法。考虑到该问题规模较小，可以得到精确解，故采用Branch and cut算法。

算法的思想是：.....（此处省略）

使用Gurobi求解器进行求解。

首先，去除环约束的LIP问题的LP松弛问题的最优解为：

```
Optimize a model with 108 rows, 883 columns and 3446 nonzeros
```

```
Model fingerprint: 0x9585e90c
```

```
Coefficient statistics:
```

```
Matrix range      [1e+00, 1e+02]
```

```
Objective range   [1e+00, 1e+00]
```

```
Bounds range      [0e+00, 0e+00]
```

```
RHS range         [1e+00, 1e+00]
```

```
Presolve removed 44 rows and 42 columns
```

```
Presolve time: 0.01s
```

```
Presolved: 64 rows, 841 columns, 3282 nonzeros
```

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	0.0000000e+00	1.002209e+02	0.000000e+00	0s
124	1.4044933e+02	0.000000e+00	0.000000e+00	0s

```
Solved in 124 iterations and 0.01 seconds
```

Optimal objective 1.404493333e+02

将其设为该TSP问题的下限；

接着，求解去除环约束的LIP问题，得到最优解；

然后，计算图中的Strong connected components（方法见《算法导论》，大致是拓扑排序+inversed graph+DFS）；

最后，将识别出的环生成约束加入到模型中，开始新一轮迭代。

Explored 12482 nodes (142033 simplex iterations) in 7.05 seconds

Thread count was 4 (of 4 available processors)

Solution count 7: 591.17 591.17 593.982 ... 830.981

Optimal solution found (tolerance 1.00e-04)

Best objective 5.911699722749e+02, best bound 5.911699722749e+02, gap 0.0000%

附录

Python代码：

```
from gurobipy import *
import pickle
import networkx as nx

# define the constants
V_NUM = 21
K_NUM = 2
ORIGIN_IDX = 5
MAX = 1e5

# load and generate basic data
f = open("../data/distance", mode="rb")
distance = pickle.load(f)
f.close()
node_list = list(range(ORIGIN_IDX - 1)) + list(range(ORIGIN_IDX, V_NUM))
dist = {(i, j, k): distance[i][j] for i in range(V_NUM) for j in range(V_NUM) for k in range(K_NUM)}
```

```

dict_linear = {(i, j, k): i*V_NUM*K_NUM + j*K_NUM + k for i in range(V_NUM) for j in
range(V_NUM) for k in range(K_NUM)}
dict_3d = mi = dict(zip(dict_linear.values(), dict_linear.keys()))

# create a model
MODEL = Model()
# MODEL.setParam('OutputFlag', 0)

# add variables
x = MODEL.addVars(dict.keys(), obj=dict, vtype=GRB.BINARY, name='x')
d = MODEL.addVar(name="d")
MODEL.update()

# set the objective
MODEL.setObjective(d + quicksum(distance[i][j] / 1.5 * x[i, j, k] for i in
range(V_NUM) for j in range(V_NUM) for k in range(K_NUM)), GRB.MINIMIZE)

# add constraints
MODEL.addConstrs(quicksum(x[i, j, k] for j in range(V_NUM) for k in range(K_NUM)) == 1
for i in node_list)
MODEL.addConstrs(quicksum(x[i, j, k] for j in range(V_NUM)) - quicksum(x[j, i, k] for
j in range(V_NUM)) == 0 for i in range(V_NUM) for k in range(K_NUM))
MODEL.addConstrs(quicksum(x[ORIGIN_IDX - 1, j, k] for j in range(V_NUM)) == 1 for k in
range(K_NUM))
MODEL.addConstrs(d - quicksum(distance[i][j] / 1.5 * x[i, j, k] for i in range(V_NUM)
for j in range(V_NUM)) >= 0 for k in range(K_NUM))
MODEL.addConstrs(x[i, i, k] == 0 for i in range(V_NUM) for k in range(K_NUM))
MODEL.addConstrs(x[i, j, k] + x[j, i, k] <= 1 for i in range(V_NUM) for j in
range(V_NUM) for k in range(K_NUM))

# callback - use lazy constraints to eliminate sub-tours
def mycallback(model, where):
    if where == GRB.Callback.MIPSOL:
        vals = model.cbGetSolution(model._vars[:-1])
        edges = list((i, j, k) for i, j, k in dict_linear.keys() if
vals[dict_linear[(i, j, k)]] > 0.5)
        shortest_cycle, k = cycle(edges)
        if shortest_cycle is not None:

```

```

        model.cbLazy(quicksum(x[i, j, k] for i in shortest_cycle for j in
shortest_cycle) <= len(shortest_cycle) - 1)

# find the loops
def cycle(edges):
    node_vehicle = {}
    G = nx.DiGraph()
    for e in edges:
        G.add_edge(e[0], e[1])
        node_vehicle[e[0]] = e[2]
        node_vehicle[e[1]] = e[2]
    shortest_subtour = None
    min = V_NUM
    cycle: list
    for cycle in nx.simple_cycles(G):
        if cycle.count(ORIGIN_IDX - 1) == 0:
            if len(cycle) < min:
                min = len(cycle)
                shortest_subtour = cycle
    if shortest_subtour is None:
        k = None
    else:
        k = node_vehicle[shortest_subtour[0]]
    return shortest_subtour, k

```

```

MODEL._vars = MODEL.getVars()
MODEL.Params.lazyConstraints = 1
MODEL.optimize(mycallback)

```

```

for v in MODEL.getVars():
    if round(v.x, 0) == 1:
        print(v)
print(MODEL.getVarByName('d'))

```

Gurobi结果:

```

Gurobi Optimizer version 9.1.2 build v9.1.2rc0 (mac64)

```

Thread count: 2 physical cores, 4 logical processors, using up to 4 threads

Optimize a model with 990 rows, 883 columns and 5168 nonzeros

Model fingerprint: 0x9d1c1028

Variable types: 1 continuous, 882 integer (882 binary)

Coefficient statistics:

Matrix range [1e+00, 1e+02]

Objective range [1e+00, 1e+02]

Bounds range [1e+00, 1e+00]

RHS range [1e+00, 1e+00]

Presolve removed 504 rows and 42 columns

Presolve time: 0.01s

Presolved: 486 rows, 841 columns, 4130 nonzeros

Variable types: 1 continuous, 840 integer (840 binary)

Root relaxation: objective 4.213480e+02, 101 iterations, 0.00 seconds

Nodes		Current Node			Objective Bounds			Work	
Expl	Unexpl	Obj	Depth	IntInf	Incumbent	BestBd	Gap	It/Node	Time
0	0	421.34800	0	46	-	421.34800	-	-	0s
0	0	491.68100	0	33	-	491.68100	-	-	0s
0	0	496.11700	0	16	-	496.11700	-	-	0s
0	0	496.11700	0	22	-	496.11700	-	-	0s
0	0	496.11700	0	16	-	496.11700	-	-	0s
0	2	496.11700	0	22	-	496.11700	-	-	0s
*	208	210		75	830.9806667	539.29700	35.1%	11.1	0s
H	268	256			816.9993333	539.29700	34.0%	12.0	0s
H	319	229			609.7846487	539.29700	11.6%	11.7	0s
H	349	224			596.8272752	539.29700	9.64%	11.5	0s
H	366	215			593.9819873	539.47579	9.18%	11.5	0s
H	793	440			591.1700000	553.88163	6.31%	12.8	1s
H	946	440			591.1699946	554.50419	6.20%	14.3	2s
H	2406	431			591.1699723	578.61373	2.12%	14.0	3s
	6245	870	cutoff	47	591.16997	583.96929	1.22%	12.3	5s

Cutting planes:

Gomory: 16

Flow cover: 6

Inf proof: 1

Zero half: 28

Mod-K: 2

RLT: 12

Lazy constraints: 2

Explored 12482 nodes (142033 simplex iterations) in 7.05 seconds

Thread count was 4 (of 4 available processors)

Solution count 7: 591.17 591.17 593.982 ... 830.981

Optimal solution found (tolerance 1.00e-04)

Best objective 5.911699722749e+02, best bound 5.911699722749e+02, gap 0.0000%

User-callback calls 26798, time in user-callback 0.19 sec

<gurobi.Var x[0,1,0] (value 0.9999995803730946)>
<gurobi.Var x[1,4,0] (value 0.9999995803565548)>
<gurobi.Var x[2,3,1] (value 1.0)>
<gurobi.Var x[3,10,1] (value 1.0)>
<gurobi.Var x[4,2,1] (value 0.9999995001976029)>
<gurobi.Var x[4,6,0] (value 0.9999995002405051)>
<gurobi.Var x[5,4,1] (value 0.9999995002630798)>
<gurobi.Var x[6,20,0] (value 0.9999995002374565)>
<gurobi.Var x[7,9,0] (value 0.999999580358502)>
<gurobi.Var x[8,18,0] (value 0.9999995806292076)>
<gurobi.Var x[9,8,0] (value 0.9999995805623223)>
<gurobi.Var x[10,11,1] (value 1.0)>
<gurobi.Var x[11,12,1] (value 1.0)>
<gurobi.Var x[12,13,1] (value 1.0)>
<gurobi.Var x[13,14,1] (value 1.0)>
<gurobi.Var x[14,5,1] (value 1.0)>
<gurobi.Var x[15,16,0] (value 0.9999995002658683)>
<gurobi.Var x[16,17,0] (value 1.0)>
<gurobi.Var x[17,0,0] (value 0.9999995001668063)>
<gurobi.Var x[18,15,0] (value 0.9999995002324273)>
<gurobi.Var x[19,7,0] (value 1.0)>
<gurobi.Var x[20,19,0] (value 0.9999990804497377)>
<gurobi.Var d (value 201.24197185085075)>

Process finished with exit code 0

