

620-362 Applied Operations Research

The Quadratic Assignment Problem (QAP)

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The Quadratic Assignment Problem (QAP)

...introduced in 1957 by Koopmans and Beckman as a model for location problems (assigning a set of economic activities to a set of locations)

...model for real-life problems:

- building layout (architectural design)
- board wiring (locating modules on the board to minimise total wire length)
- control panel and keyboard design (optimised for a language)
- machine scheduling (minimizing average job completion time)
- information retrieval (optimal ordering of data on tapes)
- analysis of chemical reactions for organic compounds
- ranking of a team in a relay race
- balancing turbine runners

QAP

QAP can be stated in the following way:

For given

$$A = (a_{ij}), \quad B = (b_{ij}), \quad \text{and} \quad C = (c_{ij})$$

real $n \times n$ matrices, find a permutation π of the set $\{1, \dots, n\}$ which minimises

$$\min_{\pi} \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{\pi(i)\pi(j)} + \sum_{i=1}^n c_{i,\pi(i)}$$

QAP

$$\min_{\pi} \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{\pi(i)\pi(j)} + \sum_{i=1}^n c_{i,\pi(i)} \quad (1)$$

- permutation π_0 which minimise (1) is called an **optimal solution**.
- the quadratic part? $\sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{\pi(i)\pi(j)}$
- the linear term? $\sum_{i=1}^n c_{i,\pi(i)}$
- size of QAP:= n
- QAP is a *combinatorial optimization* problem.
 - how many possibilities are there?

Example 1

Campus planning problem

- the University owns a piece of land on which new buildings are to be placed
- on the land n sites have been identified as *sites for the buildings*
- each building has a *special function* (library,...)

Let

a_{ij} : the walking distance between sites i and j

$A = (a_{ij})$: the *distance matrix*

b_{kl} : the number of people per week who circulate between buildings k and l

$B = (b_{kl})$: the flow matrix

Define

$\pi(i) = k$: if building k is built on site i

Example 1

- Minimising the walking distance at campus?

Now, if building k is built on site i and building l on site j , then the weekly walking distance of people who travel between building k and building l is given by

$$a_{ij}b_{\pi(i)\pi(j)}$$

Problem of assigning buildings to sites so that the walking distance between sites is minimised:

$$\min_{\pi} \sum_{i=1}^n \sum_{j=1}^n a_{ij}b_{\pi(i)\pi(j)}$$

Example 1

- Minimising the total construction cost?

c_{ik} : cost of constructing building k on site i

The cost construction minimisation problem is:

$$\min_{\pi} \sum_{i=1}^n c_{i\pi(i)}$$

Example 1

The minimisation problem whose solution satisfies both requirements is:

$$\min_{\pi} \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{\pi(i)\pi(j)} + \sum_{i=1}^n c_{i,\pi(i)}$$

Remark: π is a permutation of the set $\{1, \dots, n\}$

$\pi(i) \neq \pi(j)$, for all i, j with $i \neq j$

Example 2 (Numerical)

$$\text{Distances between sites : } A = \begin{pmatrix} 0 & 50 & 70 & 100 \\ 50 & 0 & 45 & 60 \\ 70 & 45 & 0 & 95 \\ 100 & 60 & 95 & 0 \end{pmatrix}$$

$$\text{Expected \# people commuting : } B = \begin{pmatrix} 0 & 1234 & 1050 & 900 \\ 1234 & 0 & 500 & 300 \\ 1050 & 500 & 0 & 400 \\ 900 & 300 & 400 & 0 \end{pmatrix}$$

If building i assigned to site i , i.e. $\pi(i) = i$, total weekly walking distance

$$\begin{aligned} &= 2 \times (50 \times 1234 + 70 \times 1050 + 100 \times 900 + 45 \times 500 + 60 \times \\ &\quad 300 + 95 \times 400) \\ &= 607,400 \end{aligned}$$

$$\sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{\pi(i)\pi(j)}$$

Equivalent Formulation of QAP

Definition. Let $X = (x_{ij})$ be an $n \times n$ matrix. X is called a *permutation matrix* if entries x_{ij} fulfill the following conditions:

$$\sum_{i=1}^n x_{ij} = 1, \quad 1 \leq j \leq n$$

$$\sum_{j=1}^n x_{ij} = 1, \quad 1 \leq i \leq n$$

$$x_{ij} \in \{0,1\}, \quad 1 \leq i \leq n, 1 \leq j \leq n$$

Definition. $\Pi = \{\text{set of all } n \times n \text{ permutation matrices}\}$

Equivalent Formulation of QAP

- There is one-to-one correspondence between
the set of all permutations of the set $\{1, \dots, n\}$
and
the set of $n \times n$ permutation matrices

- For the entries of $X = (x_{ij}) \in \Pi$, we specify

$$x_{ik} = \begin{cases} 1, & \text{if and only if } \pi(i) = k \\ 0, & \text{otherwise} \end{cases}$$

Equivalent Formulation of QAP

- If $\pi(i) = k$ and $\pi(j) = l$ then

$$a_{ij}b_{\pi(i)\pi(j)} = \sum_{k=1}^n \sum_{l=1}^n a_{ij}b_{kl}x_{ik}x_{jl}$$

- An equivalent formulation of QAP:

$$\min_{X \in \Pi} \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n \sum_{l=1}^n a_{ij}b_{kl}x_{ik}x_{jl} + \sum_{i=1}^n \sum_{k=1}^n c_{ik}x_{ik}$$

This is the Koopmans Beckmann formulation of the QAP.

- The formulation above is a formulation with a **quadratic objective function**.

Equivalent Formulation of QAP

$$\min_{X \in \Pi} \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n \sum_{l=1}^n a_{ij} b_{kl} x_{ik} x_{jl} + \sum_{i=1}^n \sum_{k=1}^n c_{ik} x_{ik} \equiv$$

$$\min \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n \sum_{l=1}^n a_{ij} b_{kl} x_{ik} x_{jl} + \sum_{i=1}^n \sum_{k=1}^n c_{ik} x_{ik}$$

s.t.

$$\sum_{i=1}^n x_{ij} = 1, \quad 1 \leq j \leq n$$

$$\sum_{j=1}^n x_{ij} = 1, \quad 1 \leq i \leq n$$

$$x_{ij} \in \{0,1\}, \quad 1 \leq i \leq n, 1 \leq j \leq n$$

Trace formulation of QAP

Definition. The trace of the $n \times n$ matrix A is

$$\text{tr}(A) = \sum_{i=1}^n a_{ii}$$

– for $m \times k$ matrices A and B it follows:

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \\ b_{41} & b_{42} & b_{43} \end{bmatrix}, \quad B^T = \begin{bmatrix} b_{11} & b_{21} & b_{31} & b_{41} \\ b_{12} & b_{22} & b_{32} & b_{42} \\ b_{13} & b_{23} & b_{33} & b_{43} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \\ a_{41} & a_{42} & a_{43} \end{bmatrix} \quad \text{tr}(B^T A) = \sum_{i=1}^m \sum_{j=1}^k a_{ij} b_{ij}$$

– note that the ik -entry of AXB^T is

$$(AXB^T)_{ik} = \sum_{j,l} a_{ij} x_{jl} b_{kl}$$

– and i^{th} diagonal entry of CX^T is

$$(CX^T)_{ii} = \sum_k c_{ik} x_{ik}$$

Trace formulation of QAP

It follows that

$$\begin{aligned} & \min \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n \sum_{l=1}^n a_{ij} b_{kl} x_{ik} x_{jl} + \sum_{i=1}^n \sum_{k=1}^n c_{ik} x_{ik} \\ &= \min_{X \in \Pi} \sum_{i=1}^n \sum_{k=1}^n (AXB^T)_{ik} x_{ik} + \sum_{i=1}^n (CX^T)_{ii} \\ &= \min_{X \in \Pi} \text{tr}(AXB^T + C)X^T \end{aligned}$$

This is the trace formulation of QAP introduced by Edwards in 1977.

Why use trace formulation?

Allows flexible algebraic manipulation -
lower bound calculation.

Why is lower bound needed?

Example 3

Airport gate assignment:

- airport has gates
- flights arriving and departing from gates
- known expected number of passengers transferring between flights
- known distances between gates

Objective:

Which flight is to be assigned to which gate, so as to minimise the total distance travelled by transiting passengers

Let

F = set of flights

G = set of gates

t_{ij} = expected number of passengers transferring from arriving flight i to departing flight j

d_{kl} = distance between gates k and l

Example 3

$$x_{ij} = \begin{cases} 1, & \text{flight } i \text{ is assigned to gate } k \\ 0, & \textit{otherwise} \end{cases}$$

$$\min \sum_{i \in F} \sum_{j \in F} \sum_{k \in G} \sum_{l \in G} t_{ij} d_{kl} x_{ik} x_{jl}$$

s.t.

$$\sum_{k \in G} x_{ik} = 1, \quad \forall i \in F$$

$$\sum_{i \in F} x_{ik} = 1, \quad \forall k \in G$$

$$x_{ij} \in \{0,1\}, \quad \forall i \in F, k \in G$$

Computational Complexity of QAP

- QAP is one of the most difficult combinatorial optimization problems.
- Finding an ε -approximate solution for QAP is also a hard problem.
- Practice show that QAP is extremely hard to solve to optimality.
- The computational effort to solve QAP is very likely to grow exponentially with the problem size.
- Problems of size $n \geq 20$ are currently considered as huge problems.

Linearising the QAP Model

$$y_{ijkl} = \begin{cases} 1, & i \text{ assigned to } k \text{ and } j \text{ to } l \\ 0, & \textit{otherwise} \end{cases}$$

$$\min \sum_i \sum_j \sum_k \sum_l t_{ij} d_{kl} y_{ijkl}$$

s.t.

$$\sum_i \sum_j \sum_k \sum_l y_{ijkl} = n^2$$

$$x_{ik} + x_{jl} \geq 2y_{ijkl}, \quad \forall i, j, k, l$$

$$y_{ijkl} \geq x_{ik} + x_{jl} - 1$$



- Linearised model has $n^4 + n^2$ variables and $O(n^4)$ constraints
- Solving linearised QAP is impossible (due to hardware restrictions) for larger n
- Other solution methods:
 - (meta)heuristics
 - dynamic programming
 - branch-and-bound
- Breakthroughs:
 - E.g. in 2001, a number of previously unsolved large QAPs ($20 \leq n \leq 36$) were solved to optimality on supercomputer. The problem of $n = 30$ would have took an equivalent of 7 years of computational time on a single HP9000 C3000 workstation!
 - For more updates, see <http://www.seas.upenn.edu/qaplib/>