# Advanced Algorithms for Optimization 

## Local Search

Pierre Schaus

https://github.com/pschaus/linfo2266

## Next Project: A Discrete Lot Sizing Problem

- A set of orders for each item (at most one per time-slot). Strong constraint (deadlines)
- You must produce at most one per time slot (machine) to meet the deadlines
- Stocking cost (when you produce too early) + transition cost (adaptation of the machine to minimize

Transition Costs


|  |  |  |  |
| :--- | :--- | :--- | :--- |
|  | 0 | 4 | 6 |
|  | 2 | 0 | 4 |
|  | 1 | 3 | 0 |

Stocking Costs (per day)

|  | 0 |
| :---: | :---: |
|  | 5 |
|  | 10 |

## Local Search: The idea

keep a single current state and move to neighbouring states to improve it


## Generic Local Search

- Given a initial solution $s$,
- $N(s)$ is the neighborhood of $s$.
- At a specific computation step, a neighbor may be legal or forbidden. $L(N(s), s)$ is the set of legal moves of solution $s$.
- The operator $S$ is in charge of selecting the move

```
Procedure LocalSearch(f,N,L,S,s)
    s* := s;
    for }k:=1 to MaxTrials do
        if sastifiable (s)\wedgef(s)<f(s*) then
        s*:=s;
        s:=S(L(N(s),s),s);
    return }\mp@subsup{s}{}{*
```



```
Procedure LocalSearch(f,N,L,S,s)
    \(s^{*}:=s ;\)
    for \(k:=1\) to MaxTrials do
        if sastifiable \((s) \wedge f(s)<f\left(s^{*}\right)\) then
            \(s^{*}:=s ;\)
        \(s:=S(L(N(s), s), s) ;\)
    return \(s^{*}\);
```


## The problem: Local Minima



Two solutions

1. Accept to degrade the solution (meta-heuristics)
2. Enlarge the neighborhood


- Hard Constraints (cannot be violated)
- Each number in \{1..9\} occurs $9 x$
- Soft Constraints (can be violated)
- Each number in $\{1 . .9\}$ occurs $1 x$ in a row
- Each number in \{1..9\} occurs $1 x$ in a column
- Each number in \{1..9\} occurs $1 x$ in a $3 x 3$ block


## Sudoku: Computation of violation



## Sudoku: Swap Moves 1



## Sudoku: Swap Moves 2



## Sudoku: Swap Moves 3



- Remain "more feasible" than having the right number of occurrences of each numbers:
- Some soft constraints will be come hard

- Hard Constraints (cannot be violated)
- Each number in $\{1 . .9\}$ occurs $9 x$
- Each number in $\{1 . .9\}$ occurs $1 x$ in a row
- Soft Constraints (can be violated)
- Each number in $\{1 . .9\}$ occurs $1 x$ in a block
- Each number in $\{1 . .9\}$ occurs $1 x$ in a column



## Implementation

- Using a Constrained Based Local Search (Library)
- Facilitates the development of Local Search algorithms
- you can add your constraints and objective functions
- it will compute for you the violations
- it will compute for you the delta's (what if I exchange the values of two variables)
- You can focus on the interesting part: moves and meta-heuristics. We will come back to that later, let's first understand the magic


## CBLS Sudoku Model

int[] instance1 = new int[]\{
$0,0,0,1,0,0,0,0,0$,
$0,6,0,0,7,3,0,0,4$,
$0,0,8,4,0,0,6,3,0$,
$8,0,0,6,0,0,0,9,0$,
$0,3,0,0,0,0,0,5,0$,
$0, ~ 4, ~ 0, ~ 0, ~ 0, ~ 7, ~ 0, ~ 0, ~ 2$,
$0,7,5,0,0,4,1,0,0$,
$3,0,0,9,5,0,0,7,0$,
$0,0,0,0,0,6,0,0,0\}$
IntVarLS [] grid
IntVarLS violation;
ConstraintSystem constraintSystem; ArrayList<Pair> possibleSwaps;

SolverLS ls = makeSolver();
grid $=$ makeIntVarArray(9*9, i -> makeIntVar(ls,init[i]));

$$
\begin{aligned}
& 423156789 \\
& 162973584 \\
& 128457639 \\
& 823654791 \\
& 132486759 \\
& 143957682 \\
& 275634189 \\
& 321956874 \\
& 123456789
\end{aligned}
$$

ArrayList<Constraint> constraints = new ArrayList<>() for (int $k=0 ; k<9 ; k++$ ) \{
final int $i=k$;
Constraint allDiffCol = new AllDifferent(makeIntVarArray(n, j -> grid[j * 9 + i]))
Constraint allDiffBlock = new AllDifferent(makeIntVarArray(n, j -> grid[blocks.get(i).get(j)]))
constraints.add(allDiffBlock) ;
constraints.add(allDiffCol);

## CBLS Sudoku Model

```
```

// swap two cells on the same line

```
```

// swap two cells on the same line
possibleSwaps = new ArrayList<>();
possibleSwaps = new ArrayList<>();
for (int l = 0; l < 9; l++) {
for (int l = 0; l < 9; l++) {
for (int i = 0; i< < ; i++) {
for (int i = 0; i< < ; i++) {
for (int j = i+1; j < 9; j++) {
for (int j = i+1; j < 9; j++) {
int v1 = l*9+i;
int v1 = l*9+i;
int v2 = l*9+j;
int v2 = l*9+j;
if (problem[v1] == 0 \&\& problem[v2] == 0) {
if (problem[v1] == 0 \&\& problem[v2] == 0) {
possibleSwaps.add(new Pair(v1,v2));
possibleSwaps.add(new Pair(v1,v2));
}
}
}
}
}

```
    }
```

if (problem[v1] == 0 \&\& problem[v2] == 0) \{ possibleSwaps.add(new Pair(v1,v2));

```
\}
public int swapDelta(int a, int b) \{
int before \(=\) violation.value();
public int swapDelta(int a, int \(b)\)
int before \(=\) violation.value();
    \(\operatorname{swap}(a, b)\);
    int after \(=\) violation.value();
    swap (a,b);
    return after-before;
\}
public void swap(int \(a, ~ i n t ~ b) ~\{~\)
int va \(=\) grid[a].value();
public void swap(int \(a, ~ i n t ~ b)\)
int \(v a=\) grid[a].value();
int \(v b=\) grid[b].value();
    int \(\mathrm{vb}=\) grid[b].value();
    grid[a].setValue(vb);
    grid[b].setValue(va);
\}
\(\left.\begin{array}{|l|l|l|l|l|l|l|l|}\hline 5 & 8 & 1 & 7 & 3 & 4 & 6 & 9 \\ 8 \\ \hline 2 & 9 & 7 & 6 & 8 & 1 & 2 & 5 \\ 4 \\ \hline 6 & 3 & 4 & 5 & 9 & 2 & 7 & 1\end{array}\right) 3\)


Pre-compute all the possible swap position not involving hint position

\section*{CBLS Sudoku Greedy Search}
```

public void solve() {
int iter = 1;
while (constraintSystem.violation().value() > 0){
iterationGreedy(iter++);
}
}
public void iterationGreedy(int iter) {
Pair bestSwap = bestSwap();
grid[bestSwap.a].swap(grid[bestSwap.b]);
notifyAllObservers(iter,bestSwap);
}
public Pair bestSwap() {
Pair bestSwap = null;
int bestDelta = Integer.MAX_VALUE;
for (Pair p : possibleSwaps) {
int delta = violation.getSwapDelta(grid[p.a],grid[p.b]);
if (delta < bestDelta) {
bestDelta = delta;
bestSwap = p;
}
}
return bestSwap;
}

```


OOO Objective

- Avoid direct and short cycles in order to diversify and escape from local minima


\section*{Tabu Meta Heuristic}

- From a you move to \(\mathbf{b}\) (no better choice in neighboring N )
- But the reverse move becomes tabu, you don't want to come to a for a while (duration = tabu tenure).
```

public void solve() {
int iter = 1;
int tabu = 20;
while (constraintSystem.violation().value() > 0){
iterationTabu(iter++,tabu);
return;
}
}
public void iterationTabu(int iter, int tabu) {
Pair bestSwap = bestSwapNonTabu(iter);
grid[bestSwap.a].swap(grid[bestSwap.b]);
bestSwap.iter = iter + rand.nextInt(tabu);
notifyAllObservers(iter,bestSwap);
}
public Pair bestSwapNonTabu(int iter) {
Pair bestSwap = null;
int bestDelta = Integer.MAX_VALUE;
for (Pair p : possibleSwaps) {
if (p.iter < iter) {
int delta = violation.getSwapDelta(grid[p.a],grid[p.b]);
if (delta < bestDelta) {
bestDelta = delta;
bestSwap = p;
}
}
}
return bestSwap;
}

```

\section*{Sudoku with Tabu Search}


\section*{Other possible improvements}
- Aspiration
- Maintain the current best violation
- A move is not considered tabu if it can lead to the best so far objective violation
- Restart
- Every X iterations, introduce random perturbations (for instance random swap moves)

\section*{Connected-Neighborhood}
- A neighborhood is connected if and only if for each solution s, there exists a path to an optimal solution \(\mathrm{s}^{*}\).
- Two advantages:
- You don't necessarily need a restarting strategy
- Randomized heuristics where there is a non zero probability of accepting a neighbor \(\mathrm{k} \in \mathrm{N}(\mathrm{s})\) for each solution s , may be guaranteed to reach a global optimum (example: simulated annealing).
- To prove a neighborhood is connected, you must provide an algorithm to transform any solution s1 into a solution s2 by selecting the moves allowed by the neighborhood.
- Q: Is the swap move for sudoku a connected neighborhood? Why?

CBLS Solver


\title{
Advanced Algorithms for Optimization
}

\section*{Local Search}

\author{
Part2
}

Pierre Schaus

https://github.com/pschaus/linfo2266

\section*{The problem: Local Minima}


Two solutions
1. Accept to degrade the solution (meta-heuristics)
2. Enlarge the neighborhood

TSP Move

Can you improve this tour?


\section*{2 Opt}


Disconnect by removing two edges, and re-construct the tour.

Euclidian TSP: optimal solution cannot have crossing edges. This move will avoid to have crossing edges.

\section*{2 Opt Evolution}


\section*{Is 2-Opt a connected?}
- Is the 2Opt move a connected neighbourhood for the TSP?

\[
1,2,3,5,6,7,8,4,9,10,11
\]

\section*{2-Opt and connectivity}

\(3,1,2,4,7,6,5,8,9,11,10\)
assume this is the optimal solution \(s^{*}\), given a current solution \(s\), can you find a sequence of 2-opt move to transform s into \(\mathrm{s}^{*}\) ?

\section*{Working example}


\section*{Question}
- We know that In a Euclidien TSP, if the current solution has two crossing edges, it can be improved with a single 2-OPT move.
- But if the current solution has no crossing edges, does it mean that it can't be improve by a 2-OPT move?


\section*{Answer}


\section*{Implementing 2-Opt: Generic Framework}
```

static abstract class TSPLocalSearch {
int n;
int [][] dist;
int [] tourSaved
TSPLocalSearch(TSPInstance data) {
this.n = data.n;
this.dist = data.distanceMatrix
this.tour = new int[data.n+1]; // first and last node are the same
for (int i = 0; i < n; i++)
tour[i] = i;
tourSaved = Arrays.copyOf(tour,n+1)
}
public int[] currentTour() {
return Arrays.copyOf(tour,n+1);
}
public void saveTour() {
System.arraycopy(tour,0,tourSaved,0,n+1);
}
public void restoreSaved() {
System.arraycopy(tourSaved,0,tour, 0, n+1);
}
abstract boolean iteration();
public void optimize() {
int iter = 0;
long t0 = System.currentTimeMillis();
boolean improved = false
do
improved = iteration()
iter += 1
} while (improved)
}
}

```
https://github.com/pschaus/linfo2266
```

public int deltaTwoOpt(int left, int right) {
int distLeft = dist[tour[left]][tour[left+1]];
int distRight = dist[tour[right]][tour[right+1]];
int distLeftNew = dist[tour[left]][tour[right]];
int distRightNew = dist[tour[left+1]][tour[right+1]];
return distLeftNew + distRightNew - distLeft - distRight;
}

```

- Our tour representation is (artificially) « oriented » in our implementation

```

public void twoOpt(int left, int right) {
for (int k = 0; k < (right - left + 1) / 2; k++) {
int tmp = tour[left + 1 + k];
tour[left + k + 1] = tour[right - k];
tour[right - k] = tmp;
}
}

```
\begin{tabular}{c|c|c|c|c|c|c|c|c}
0 & 1 & \(\ldots\) & left & left+1 & \(\ldots\) & right & right+1 & \\
\hline & & & A & B & \(\ldots\) & C & D & \\
\hline
\end{tabular}

Effect of twoOpt is to swap this sub-array time: O(n)

TSP2Opt

\section*{boolean iteration() \{}
int bestLeft \(=0\), bestRight \(=0\), bestDelta \(=0\);
// 2-opt move
for (int left \(=0\); left \(<n\); left++) \{ for (int right = left+1; right \(<\mathrm{n}\); right++) \{
            int delta \(=\) deltaTwoOpt(left,right);
            if (delta < bestDelta) \{
                bestDelta = delta;
                bestLeft = left;
                bestRight \(=\) right;
            \}
        \}
    \}
    twoOpt(bestLeft, bestRight);
    return bestDelta < 0;
\}
- The neighbourhood is the set of all tours that can be obtained by removing 3 edges.


\section*{Let us dream ...}
- What about a K-Opt but the K can choose it-self.
- Sometime K can be 2 , sometimes 5 , etc.
- Would it be tractable?

- NO: General K-Opt is computationally too intensive
- But we can limit our-self to a particular form of k-Opt moves: Sequential K-Opt moves
- A K-Opt move is called sequential if it can be described by a path alternating between deleted and added edges.

Example: sequential 6-Opt


\section*{Lin-Kernighan}
- Sequential K-Opt moves: What values for k ?
- The idea is to build greedily a K-Opt move
- At each step we compute the « gain » of applying it.
- The \((k+1)\)-sequential move is an extension of the \(k\)-sequential move, etc
- Then we select (retrospectively) the \(k\) that gives the best « gain »


\section*{Observation:}
- A sequential k-Opt move has the same effect as \(\mathrm{k}-1\) 2Opt Moves.
- Example: sequential 4-Opt \(=2 \mathrm{Opt}+2 \mathrm{Opt}+2 \mathrm{Opt}\)


Sequential 4 -opt move performed by three 2-opt moves. Close-up edges are shown by dashed lines

K-Opt starting at 0


K-Opt starting at 0


K-Opt starting at 0


K-Opt starting at 0


\section*{K-Opt starting at 8}


Do a K-Opt iteration starting from 8, do at-least 2, you should see something very nice after two iterations (that 2-Opt alone cannot see)


\section*{Implementing K-Opt}
```

static class TSPKOpt extends TSPLocalSearch {
int K;
TSPKOpt(TSPInstance data, int K) {
super(data);
this.K = K;
}
public boolean kOptFrom(int i) {
...
}
@Override
boolean iteration() {
var found = false;
for (int i = 0; i < n; i++) {
if (kOptFrom(i)) {
found = true;
}
}
return found;
}
}

```

\section*{Implementing K-Opt:}
public boolean kOptFrom(int i) \{
saveTour();
int cumulatedDelta \(=0\);
int bestCumulatedDelta = cumulatedDelta;
int bestK \(=0\);
int \(k=0 ;\)
int prev \(=-1\);
do \{
k += 1;
int bestDelta = Integer.MAX_VALUE;
int bestj \(=-1\);
for (int \(j=0 ; j<n ; j++)\{\)
int dist \(=\) Math.abs(j-i);
if (1 < dist \(\& \&\) dist \(<\mathrm{n}-1 \& \& j \operatorname{l}=\mathrm{prev})\{/ /\) no stupid 2-opt or direct cycling
int delta = deltaTwoOpt(i,j);
if (delta < bestDelta) \{ bestDelta = delta; bestj = j;
\}
\}
\}
prev = bestj
twoopt(i,bestj)
cumulatedDelta \(+=\) bestDelta;
if (cumulatedDelta < bestCumulatedDelta) \{ bestCumulatedDelta = cumulatedDelta;
bestK = k; saveTour();
\}
\} while (k < K) ;
restoreSaved();
return bestCumulatedDelta < 0;


\section*{ATSP reduction to TSP}
- The distance matrix is not always symmetric (city: one-way roads, etc).
- Possible to transform an ATSP into a TSP by doubling the number of nodes.


1 to 1 correspondance

\section*{ATSP reduction to TSP}
- Idea: N-N' are so attractive (large negative number) that they are part of any optimal TSP. Hence A'B and AB' cannot be both selected otherwise there would be a sub-tour (not hamiltonian circuit).


1 to 1 correspondance

\section*{Vehicle Routing}

- Given vehicles starting from a depot each having a fixed capacity C
- How to visit each customer once without exceeding the capa (we charge a quantity at each customer) while minimizing the total distance?

\section*{Two strategies for initialization}
- VRP = partitioning (trucs) + sequencing (circuits)
- We usually use two strategies:
- Partition first:
- Build one group of nodes per vehicle (clustering)
- Solve the TSP on each group
- Sequence first:
- Relax the vehicle capacity and solve a giant TSP
- Split the giant TSP into trip satisfying the capacity constraints.

\section*{Partition vs Sequence first}

1. Let \(S\) be a solution comprising \(r=n\) routes, each of which serving a demand node (with one deliveryman).
2. (Savings computation) Compute the savings in distance resulting from serving the pair of nodes \(i\) and \(j(i \neq j)\) in the same route (that is, \(\left.s_{i j}=d_{i 1}+d_{1 j}-d_{i j}\right)\), and store the resulting values (ordered in a non increasing fashion) in a list \(\mathcal{L}\).
3. While \(\mathcal{L} \neq \emptyset\) :
3.1. Starting from the first element of \(\mathcal{L}\), select the pair of nodes \(i\) and \(j\) that satisfies one of the following conditions:
a) Neither \(i\) 's nor \(j\) 's routes have already been merged. In this case, merging would include both \(i\) and \(j\) in the same route.
b) Exactly one of the two nodes' routes ( \(i\) 's or \(j\) 's) has already been merged and the corresponding node is not interior to that route. In this case, the link \(i-j\) would be added to that same route.
c) Both \(i\) 's and \(j\) 's routes are distinct from each other, have already been merged, and neither node is interior to its route. In this case, the two routes would be merged.
3.2. Obtain a new solution \(S\) by implementing the selected merge, rescheduling the resulting route, and making \(r=r-1\) if the vehicle capacity and maximum route time constraints are not violated.
3.3. Eliminate the element associated to the selected merge from \(\mathcal{L}\).
4. Return solution \(S\).

Figure 1 - Sequential savings algorithm (SAV).

\section*{VRP Initialization: Saving Heuristics Clarke and Wright 1964}
- Start with as many vehicles as the number of customers
- Insert customers and merge routes such that the capa is not violated and the distance is decreased the most

(a)

(d)

(b)

(e)

(c)

(f)

\section*{VRP Initialization: Sweep Heuristic}
- A ray centered at the depot performs a full rotation, collecting customers into clusters not violating the capacity

(a)

(d)

(b)

(e)

(c)

(f)

Initial TSP Giant Tour that violates the capacity 10 for one truck
1. Giant tour \(T=(1,2,3,4,5)\) with demands


How to discover this split optimally?

3. Optimal splitting, cost 205

\section*{Answer: Dynamic Programming}

1. Giant tour \(T=(1,2,3,4,5)\) with demands

3. Optimal splitting, cost 205

2. Auxiliary graph \(H\) of possible trips for \(Q=10\) - Shortest path in bold

\section*{Shortest Path: Bellman Algo}


\section*{Implementation}

Auxiliary graph \(H=(X, A, Z)\) with \(n+1\) nodes numbered rom 0 . A feasible route \(\left(T_{i+1}, \ldots, T_{j}\right)\) is modelled by arc \((i-1, j)\).

Bellman's algorithm for directed acyclic graphs (DAGs). Compact form with implicit auxiliary graph (Prins, 2004):
```

set }\mp@subsup{V}{0}{}\mathrm{ to 0 and other labels }\mp@subsup{V}{i}{}\mathrm{ to m (cost of path to node i)

```
for \(i \leftarrow 1\) to \(n\) do
    for \(j \leftarrow i\) to \(n\) while subsequence/route \(\left(T_{i}, T_{i+1}, \ldots, T_{j}\right)\) feasible
        compute route cost, i.e., cost \(z_{i-1, j}\) of arc (i-1,j)
        if \(V_{i-1}+z_{i-1, j}<V_{j}\) then
            \(V_{j} \leftarrow V_{i-1}+z_{i-1, j}\)
        endif
    endfor
endfor
- The giant tour T can be built using any TSP algorithm.
- Optimal TSP tours do not necessarily lead to optimal CVRP solutions after splitting, good tours are enough.
- However, Split is optimal, subject to the ordering of \(T\)
- \(O\left(n^{\wedge} 2\right)\) time complexity overall (capacity check in \(O(1)\) )

Nearest Neighbor heuristic (NN), well known for the TSP. Randomized version:


Draw the next client \(j\) among the \(K\) nearest ones.

\section*{Scheduling Moves}
- Given a set of non preemptive activities (cannot be interrupted)

- A resource with capa C
duration
- How to schedule them to minimize the total duration (makespan) without exceeding the capacity of
 the resource?


\section*{Scheduling with capa: IFlat-IRelax algorithm}
- Iterate between two steps:
1. flatten = add strong precedences constraints until the capacity constraint is satisfied (assuming each activity starts as soon as possible while satisfying the precedence constraints)
2. relax = remove some precedences randomly on the critical path

Example

\section*{\(\mathrm{C}=20\)}

\(\begin{array}{llllll}1 & 2 & 3 & 4 & 5 & 6\end{array}\)
\begin{tabular}{cccccc}
10 & 16 & 14 & 13 & 21 & 5 \\
7 & 7 & 4 & 10 & 4 & 9
\end{tabular}
each activity scheduled at its earliest start while satisfying the precedences (dynamic programming)

\section*{makespan}

\section*{current precedence graph}

critical path = the path that causes the makespan value
to have a chance to decrease the makespan we have to relax precedences on the critical path (say we remove 6->2)

\section*{Example}

current precedence graph

critical path = the path that causes the makespan value

\section*{Eternity II}
- \(16 x 16\) edge matching puzzle
- \(2 \$\) millions if you solve it ...


\section*{What do you suggest as neighborhood?}

\section*{Objective: maximize \# correct connections (480)}


\section*{What do you suggest as neighborhood?}

\section*{Swap and rotate pieces pairwise?}


\section*{Let's try to move >2 pieces at once}


\section*{Generalization of Swap and Rotate}
- Remove \(m\) pieces from non edge adjacent positions (up to \(\mathrm{n}^{2} / 2=\) chessboard)..
- Replace them optimally.
- This neighborhood can be solved optimally and efficiently
- Let's remove 5 non adjacent pieces
- Let's remove 5 non adjacent pieces

- Compute score to place them each optimally in holes

- Compute score to place them each optimally in holes
- At the end, a complete weighted bipartite graph between removed pieces and holes.
- solve a maximum assignment problem (Hungarian algorithm in \(\mathrm{O}\left(\mathrm{m}^{3}\right)\) ).
- The arcs in the assignment and the label of the arcs tell us how to replace optimally the pieces in the holes.
- Neighborhood of size: \(m!4 m\) (exponential) but it is optimally explored in polynomial time.
- Each step, \(m\) non-adjacent positions are randomly chosen and the move is applied. During 30 seconds. Random initial positions of the pieces on the board.


\section*{Exam Questions}
- Be able to explain the principle of local search
- Be able to implement a simple search with swap-moves and a tabu-search metaheuristic
- Be able to suggest a neighborhood for a new problem and discuss/prove it it is connected or not.
- Be able to explain and apply moves for:
- TSP (Lin-Kernighan) and vehicle routing,
- scheduling,
- eternity
- Implementing the Lin-Kernighan heuristic for the TSP, Markus Reuther
- General k-opt submoves for the Lin-Kernighan TSP heuristic, Keld Helsgaun
- Optimization approaches for the vip's with black box feasibility. Florence Massen. PhD thesis 2013.
- In pursuit of the traveling salesman, William J. Cook, 2012.
- Constrained Based Local Search. P. Van Hentenryck and L. Michel. 2006.
- Hybrization of CP and VLNS for eternity II. P Schaus and Yves Deville.
- Iterative Relaxations for Iterative Flattening in Cumulative Scheduling. P. Van Hentenryck and L. Michel. 2006.
- Prins, C., Labadi, N., \& Reghioui, M. (2009). Tour splitting algorithms for vehicle routing problems. International Journal of Production Research, 47(2), 507-535.

\section*{Inventors}

\section*{Brian Wilson Kernighan}


1942

also coauthor of the AWK and AMPL programming languages

Fred Glover


1937
```

