Iterative Improvement

Algorithm design technique for solving optimization problems

Start with a feasible solution

Repeat the following step until no improvement can be found:
  • change the current feasible solution to a feasible solution with a better value of the objective function

Return the last feasible solution as optimal

Note: Typically, a change in a current solution is “small”

(local search)

Major difficulty: Local optimum vs. global optimum
Important Examples

- simplex method
- Ford-Fulkerson algorithm for maximum flow problem
- maximum matching of graph vertices
- Gale-Shapley algorithm for the stable marriage problem
- local search heuristics
Linear programming (LP) problem is to optimize a linear function of several variables subject to linear constraints:

maximize (or minimize) $c_1 x_1 + ... + c_n x_n$

subject to

$a_{i1} x_1 + ... + a_{in} x_n \leq (or \geq or =) b_i, \ i = 1,...,m$

$x_1 \geq 0, \ ... \ , x_n \geq 0$

The function $z = c_1 x_1 + ... + c_n x_n$ is called the objective function;

constraints $x_1 \geq 0, \ ... \ , x_n \geq 0$ are called nonnegativity constraints
Example

maximize \( 3x + 5y \)
subject to \( x + y \leq 4 \)
\( x + 3y \leq 6 \)
\( x \geq 0, y \geq 0 \)

Feasible region is the area bounded by the constraints:
- \( x + y = 4 \) at \((4, 0)\)
- \( x + 3y = 6 \) at \((0, 2)\)
- \( x = 0 \) at \((0, 0)\)
- \( y = 0 \) at \((3, 1)\)
Geometric solution

maximize \[3x + 5y\]
subject to \[x + y \leq 4\]
\[x + 3y \leq 6\]
\[x \geq 0, y \geq 0\]

Optimal solution: \(x = 3, y = 1\)

Extreme Point Theorem Any LP problem with a nonempty bounded feasible region has an optimal solution; moreover, an optimal solution can always be found at an extreme point of the problem's feasible region.
3 possible outcomes in solving an LP problem

- has a finite optimal solution, which may no be unique
- **unbounded**: the objective function of maximization (minimization) LP problem is unbounded from above (below) on its feasible region
- **infeasible**: there are no points satisfying all the constraints, i.e. the constraints are contradictory
The Simplex Method

The classic method for solving LP problems;

one of the most important algorithms ever invented

Invented by George Dantzig in 1947

Based on the iterative improvement idea:

Generates a sequence of adjacent points of the problem’s feasible region with improving values of the objective function until no further improvement is possible
Standard form of LP problem

must be a maximization problem

all constraints (except the nonnegativity constraints)
must be in the form of linear equations
all the variables must be required to be nonnegative

Thus, the general linear programming problem in standard
form with \( m \) constraints and \( n \) unknowns \( (n \geq m) \) is

\[
\text{maximize } c_1 x_1 + \ldots + c_n x_n \\
\text{subject to } a_{i1}x_1 + \ldots + a_{in} x_n = b_i, \; i = 1, \ldots, m, \; x_1 \geq 0, \ldots, x_n \geq 0
\]

Every LP problem can be represented in such form
Example

maximize \( 3x + 5y \) \hspace{1cm} \text{maximize } 3x + 5y + 0u + 0v

subject to \( x + y \leq 4 \) \hspace{1cm} \text{subject to } x + y + u = 4

\hspace{1cm} x + 3y \leq 6 \hspace{1cm} \text{subject to } x + 3y + v = 6

\hspace{1cm} x \geq 0, \ y \geq 0 \hspace{1cm} \hspace{1cm} x \geq 0, \ y \geq 0, \ u \geq 0, \ v \geq 0

Variables \( u \) and \( v \), transforming inequality constraints into equality constrains, are called \textit{slack variables}
A basic solution to a system of \( m \) linear equations in \( n \) unknowns \((n \geq m)\) is obtained by setting \( n - m \) variables to 0 and solving the resulting system to get the values of the other \( m \) variables. The variables set to 0 are called nonbasic; the variables obtained by solving the system are called basic. A basic solution is called feasible if all its (basic) variables are nonnegative.

Example \( x + y + u = 4 \)
\[ x + 3y + v = 6 \]

(0, 0, 4, 6) is basic feasible solution

\( (x, y \text{ are nonbasic; } u, v \text{ are basic}) \)

There is a 1-1 correspondence between extreme points of LP’s feasible region and its basic feasible solutions.
maximize \( z = 3x + 5y + 0u + 0v \)

subject to \( x + y + u = 4 \)
\( x + 3y + v = 6 \)
\( x \geq 0, \ y \geq 0, \ u \geq 0, \ v \geq 0 \)

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basic feasible solution
\((0, 0, 4, 6)\)

value of \( z \) at \((0, 0, 4, 6)\)
Outline of the Simplex Method

Step 0 [Initialization] Present a given LP problem in standard form and set up initial tableau.

Step 1 [Optimality test] If all entries in the objective row are nonnegative — stop: the tableau represents an optimal solution.

Step 2 [Find entering variable] Select (the most) negative entry in the objective row. Mark its column to indicate the entering variable and the pivot column.

Step 3 [Find departing variable] For each positive entry in the pivot column, calculate the $\theta$-ratio by dividing that row's entry in the rightmost column by its entry in the pivot column. (If there are no positive entries in the pivot column — stop: the problem is unbounded.) Find the row with the smallest $\theta$-ratio, mark this row to indicate the departing variable and the pivot row.

Step 4 [Form the next tableau] Divide all the entries in the pivot row by its entry in the pivot column. Subtract from each of the other rows, including the objective row, the new pivot row multiplied by the entry in the pivot column of the row in question. Replace the label of the pivot row by the variable's name of the pivot column and go back to Step 1.
Example of Simplex Method Application

maximize  \[ z = 3x + 5y + 0u + 0v \]
subject to  \[
\begin{align*}
    x + y + u &= 4 \\
    x + 3y + v &= 6 \\
    x &\geq 0, \quad y &\geq 0, \quad u &\geq 0, \quad v &\geq 0
\end{align*}
\]

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basic feasible sol.  \((0, 0, 4, 6)\)
\[ z = 0 \]

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basic feasible sol.  \((0, 2, 2, 0)\)
\[ z = 10 \]

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<td>0</td>
<td>2</td>
<td>1</td>
<td>14</td>
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</tbody>
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basic feasible sol.  \((3, 1, 0, 0)\)
\[ z = 14 \]
Notes on the Simplex Method

Finding an initial basic feasible solution may pose a problem

Theoretical possibility of cycling

Typical number of iterations is between $m$ and $3m$, where $m$ is the number of equality constraints in the standard form

Worse-case efficiency is exponential

More recent interior-point algorithms such as Karmarkar’s algorithm (1984) have polynomial worst-case efficiency and have performed competitively with the simplex method in empirical tests.
Maximum Flow Problem

Problem of maximizing the flow of a material through a transportation network (e.g., pipeline system, communications or transportation networks)

Formally represented by a connected weighted digraph with \( n \) vertices numbered from 1 to \( n \) with the following properties:

- contains exactly one vertex with no entering edges, called the source (numbered 1)
- contains exactly one vertex with no leaving edges, called the sink (numbered \( n \))
- has positive integer weight \( u_{ij} \) on each directed edge \( (i,j) \), called the edge capacity, indicating the upper bound on the amount of the material that can be sent from \( i \) to \( j \) through this edge
Example of Flow Network

Source

1 -- 2 -- 3 -- 6

3 -- 2

3

2

4

Sink

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Definition of a Flow

A flow is an assignment of real numbers \( x_{ij} \) to edges \((i,j)\) of a given network that satisfy the following:

**flow-conservation requirements**

The total amount of material entering an intermediate vertex must be equal to the total amount of the material leaving the vertex

\[
\sum x_{ji} = \sum x_{ij} \text{ for } i = 2, 3, \ldots, n-1
\]

**capacity constraints**

\[0 \leq x_{ij} \leq u_{ij} \text{ for every edge } (i,j) \in E\]
Since no material can be lost or added to by going through intermediate vertices of the network, the total amount of the material leaving the source must end up at the sink:

\[ \sum x_{1j} = \sum x_{jn} \]

The value of the flow is defined as the total outflow from the source (= the total inflow into the sink).

The *maximum flow problem* is to find a flow of the largest value (maximum flow) for a given network.
Maximum-Flow Problem as LP problem

Maximize \( v = \sum_{j: (1,j) \in E} x_{1j} \)

subject to

\[
\sum_{j: (j,i) \in E} x_{ji} - \sum_{j: (i,j) \in E} x_{ij} = 0 \quad \text{for } i = 2, 3, \ldots, n-1
\]

\( 0 \leq x_{ij} \leq u_{ij} \quad \text{for every edge } (i,j) \in E \)
Augmenting Path (Ford-Fulkerson) Method

Start with the zero flow ($x_{ij} = 0$ for every edge)

On each iteration, try to find a flow-augmenting path from source to sink, which a path along which some additional flow can be sent

If a flow-augmenting path is found, adjust the flow along the edges of this path to get a flow of increased value and try again

If no flow-augmenting path is found, the current flow is maximum
Example 1

Augmenting path: 1→2→3→6
Example 1 (cont.)

Augmenting path: $1 \rightarrow 4 \rightarrow 3 \leftarrow 2 \rightarrow 5 \rightarrow 6$
Example 1 (maximum flow)

max flow value = 3
Finding a flow-augmenting path

To find a flow-augmenting path for a flow $x$, consider paths from source to sink in the underlying undirected graph in which any two consecutive vertices $i,j$ are either:

- connected by a directed edge ($i$ to $j$) with some positive unused capacity $r_{ij} = u_{ij} - x_{ij}$  
  – known as forward edge ()

  OR

- connected by a directed edge ($j$ to $i$) with positive flow $x_{ji}$  
  – known as backward edge ()

If a flow-augmenting path is found, the current flow can be increased by $r$ units by increasing $x_{ij}$ by $r$ on each forward edge and decreasing $x_{ji}$ by $r$ on each backward edge, where

$$r = \min \left\{ r_{ij} \text{ on all forward edges}, \ x_{ji} \text{ on all backward edges} \right\}$$

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Finding a flow-augmenting path (cont.)

Assuming the edge capacities are integers, $r$ is a positive integer.

On each iteration, the flow value increases by at least 1.

Maximum value is bounded by the sum of the capacities of the edges leaving the source; hence the augmenting-path method has to stop after a finite number of iterations.

The final flow is always maximum, its value doesn’t depend on a sequence of augmenting paths used.
Performance degeneration of the method

The augmenting-path method doesn’t prescribe a specific way for generating flow-augmenting paths. Selecting a bad sequence of augmenting paths could impact the method’s efficiency.

Example 2

U = large positive integer
Requires 2U iterations to reach maximum flow of value 2U
Shortest-Augmenting-Path Algorithm

Generate augmenting path with the least number of edges by BFS as follows.
Starting at the source, perform BFS traversal by marking new (unlabeled) vertices with two labels:

- first label – indicates the amount of additional flow that can be brought from the source to the vertex being labeled
- second label – indicates the vertex from which the vertex being labeled was reached, with “+” or “−” added to the second label to indicate whether the vertex was reached via a forward or backward edge
Vertex labeling

The source is always labeled with $\infty,-$.

All other vertices are labeled as follows:

- If unlabeled vertex $j$ is connected to the front vertex $i$ of the traversal queue by a directed edge from $i$ to $j$ with positive unused capacity $r_{ij} = u_{ij} - x_{ij}$ (forward edge), vertex $j$ is labeled with $l_j, i^+$, where $l_j = \min\{l_i, r_{ij}\}$

- If unlabeled vertex $j$ is connected to the front vertex $i$ of the traversal queue by a directed edge from $j$ to $i$ with positive flow $x_{ji}$ (backward edge), vertex $j$ is labeled $l_j, i^-$, where $l_j = \min\{l_i, x_{ji}\}$
Vertex labeling (cont.)

If the sink ends up being labeled, the current flow can be augmented by the amount indicated by the sink’s first label.

The augmentation of the current flow is performed along the augmenting path traced by following the vertex second labels from sink to source; the current flow quantities are increased on the forward edges and decreased on the backward edges of this path.

If the sink remains unlabeled after the traversal queue becomes empty, the algorithm returns the current flow as maximum and stops.
Augment the flow by 2 (the sink’s first label) along the path 1→2→3→6
Augment the flow by 1 (the sink’s first label) along the path $1 \rightarrow 4 \rightarrow 3 \leftarrow 2 \rightarrow 5 \rightarrow 6$
Example (cont.)

Queue: 1 4
↑ ↑

No augmenting path (the sink is unlabeled)
the current flow is maximum

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Definition of a Cut

Let $X$ be a set of vertices in a network that includes its source but does not include its sink, and let $\overline{X}$, the complement of $X$, be the rest of the vertices including the sink. The cut induced by this partition of the vertices is the set of all the edges with a tail in $X$ and a head in $\overline{X}$. Capacity of a cut is defined as the sum of capacities of the edges that compose the cut.

We’ll denote a cut and its capacity by $C(X,\overline{X})$ and $c(X,\overline{X})$.

Note that if all the edges of a cut were deleted from the network, there would be no directed path from source to sink.

Minimum cut is a cut of the smallest capacity in a given network.
Examples of network cuts

If $X = \{1\}$ and $X^- = \{2,3,4,5,6\}$, $C(X,X^-) = \{(1,2), (1,4)\}$, $c = 5$

If $X = \{1,2,3,4,5\}$ and $X^- = \{6\}$, $C(X,X^-) = \{(3,6), (5,6)\}$, $c = 6$

If $X = \{1,2,4\}$ and $X^- = \{3,5,6\}$, $C(X,X^-) = \{(2,3), (2,5), (4,3)\}$, $c = 9$
Max-Flow Min-Cut Theorem

The value of maximum flow in a network is equal to the capacity of its minimum cut.

The shortest augmenting path algorithm yields both a maximum flow and a minimum cut:
- maximum flow is the final flow produced by the algorithm.
- minimum cut is formed by all the edges from the labeled vertices to unlabeled vertices on the last iteration of the algorithm.
- all the edges from the labeled to unlabeled vertices are full, i.e., their flow amounts are equal to the edge capacities, while all the edges from the unlabeled to labeled vertices, if any, have zero flow amounts on them.
Shortest-augmenting-path algorithm
Input: A network with single source $s$, single sink $t$, and positive integer capacities $u_{ij}$ on its edges $(i,j)$
Output: A maximum flow $x$
assign $x_{ij} = 0$ to every edge $(i,j)$ in the network
label the source with $\infty$, − and add the source to the empty queue $Q$
while not Empty($Q$) do
  $i \leftarrow$ Front($Q$); Dequeue($Q$)
  for every edge from $i$ to $j$ do //forward edges
    if $j$ is unlabeled
      $r_{ij} \leftarrow u_{ij} - x_{ij}$
      if $r_{ij} > 0$
        $l_j \leftarrow \min\{l_i, r_{ij}\}$; label $j$ with $l_j, i^+$
        Enqueue($Q, j$)
  for every edge from $j$ to $i$ do //backward edges
    if $j$ is unlabeled
      if $x_{ji} > 0$
        $l_j \leftarrow \min\{l_i, x_{ji}\}$; label $j$ with $l_j, i^-$
        Enqueue($Q, j$)
if the sink has been labeled
  //augment along the augmenting path found
  $j \leftarrow t$ //start at the sink and move backwards using second labels
  while $j \neq s$ //the source hasn’t been reached
    if the second label of vertex $j$ is $i^+$
      $x_{ij} \leftarrow x_{ij} + l_n$
    else //the second label of vertex $j$ is $i^-$
      $x_{ji} \leftarrow x_{ji} - l_n$
    $j \leftarrow i$
  erase all vertex labels except the ones of the source
  reinitialize $Q$ with the source
return $x$ //the current flow is maximum
The number of augmenting paths needed by the shortest-augmenting-path algorithm never exceeds $nm/2$, where $n$ and $m$ are the number of vertices and edges, respectively.

Since the time required to find shortest augmenting path by breadth-first search is in $O(n+m)=O(m)$ for networks represented by their adjacency lists, the time efficiency of the shortest-augmenting-path algorithm is in $O(nm^2)$ for this representation.

More efficient algorithms have been found that can run in close to $O(nm)$ time, but these algorithms don’t fall into the iterative-improvement paradigm.
Bipartite Graphs

*Bipartite graph*: a graph whose vertices can be partitioned into two disjoint sets $V$ and $U$, not necessarily of the same size, so that every edge connects a vertex in $V$ to a vertex in $U$.

A graph is bipartite if and only if it does not have a cycle of an odd length.
A bipartite graph is 2-colorable: the vertices can be colored in two colors so that every edge has its vertices colored differently.

\[ \begin{align*}
  V & : 1 \rightarrow \text{red}, 2 \rightarrow \text{red}, 3 \rightarrow \text{red}, 4 \rightarrow \text{red}, 5 \rightarrow \text{red} \\
  U & : 6 \rightarrow \text{blue}, 7 \rightarrow \text{blue}, 8 \rightarrow \text{blue}, 9 \rightarrow \text{blue}, 10 \rightarrow \text{blue}
\end{align*} \]
Matching in a Graph

A matching in a graph is a subset of its edges with the property that no two edges share a vertex. A matching in this graph $M = \{(4,8), (5,9)\}$.

A maximum (or maximum cardinality) matching is a matching with the largest number of edges. It always exists but is not always unique.
Free Vertices and Maximum Matching

For a given matching $M$, a vertex is called free (or unmatched) if it is not an endpoint of any edge in $M$; otherwise, a vertex is said to be matched

- If every vertex is matched, then $M$ is a maximum matching
- If there are unmatched or free vertices, then $M$ may be able to be improved
- We can immediately increase a matching by adding an edge connecting two free vertices (e.g., $(1,6)$ above)
An *augmenting path* for a matching $M$ is a path from a free vertex in $V$ to a free vertex in $U$ whose edges alternate between edges not in $M$ and edges in $M$. The length of an augmenting path is always odd. Adding to $M$ the odd numbered path edges and deleting from it the even numbered path edges increases the matching size by 1 (augmentation). One-edge path between two free vertices is a special case of augmenting path.

Augmentation along path $2, 6, 1, 7$. 

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Augmenting Paths (another example)

Augmentation along
3, 8, 4, 9, 5, 10

• Matching on the right is maximum (*perfect* matching)
• **Theorem** A matching M is maximum if and only if there exists
  no augmenting path with respect to M
Augmenting Path Method (template)

Start with some initial matching
  • e.g., the empty set

Find an augmenting path and augment the current matching along that path
  • e.g., using breadth-first search like method

When no augmenting path can be found, terminate and return the last matching, which is maximum
BFS-based Augmenting Path Algorithm

Initialize queue Q with all free vertices in one of the sets (say V)

While Q is not empty, delete front vertex \( w \) and label every unlabeled vertex \( u \) adjacent to \( w \) as follows:

Case 1 (\( w \) is in V)
- If \( u \) is free, augment the matching along the path ending at \( u \) by moving backwards until a free vertex in V is reached. After that, erase all labels and reinitialize Q with all the vertices in V that are still free
- If \( u \) is matched (not with \( w \)), label \( u \) with \( w \) and enqueue \( u \)

Case 2 (\( w \) is in U) Label its matching mate \( v \) with \( w \) and enqueue \( v \)

After Q becomes empty, return the last matching, which is maximum
Example (revisited)

Initial Graph

V
1 2 3 4 5

U
6 7 8 9 10

Queue: 1 2 3

Resulting Graph

V
1 2 3 4 5

U
6 7 8 9 10

Queue: 1 2 3

Augment from 6

Each vertex is labeled with the vertex it was reached from. Queue deletions are indicated by arrows. The free vertex found in U is shaded and labeled for clarity; the new matching obtained by the augmentation is shown on the next slide.
Example (cont.)

Initial Graph

V
1 2 3 4 5

U
6 7 8 9 10

Queue: 2 3

Resulting Graph

V
1 2 3 4 5

U
6 7 8 9 10

Queue: 2 3 6 8 1 4

Augment from 7
Example (cont.)

Initial Graph

Queue: 3

Resulting Graph

Queue: 3 6 8 2 4 9

Augment from 10

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Example: maximum matching found

This matching is maximum since there are no remaining free vertices in V (the queue is empty)

Note that this matching differs from the maximum matching found earlier
Maximum-matching algorithm for bipartite graphs
Input: A bipartite graph \( G = (V, U, E) \)
Output: A maximum-cardinality matching \( M \) in the input graph
initialize set \( M \) of edges with some valid matching (e.g., the empty set)
initialize queue \( Q \) with all the free vertices in \( V \) (in any order)
\[ \textbf{while not Empty}(Q) \textbf{ do} \]
\[ w \leftarrow \text{Front}(Q); \text{ Dequeue}(Q) \]
\[ \text{if } w \in V \]
\[ \text{for every vertex } u \text{ adjacent to } w \text{ do} \]
\[ \text{if } u \text{ is free} \]
\[ \text{//augment} \]
\[ M \leftarrow M \cup (w, u) \]
\[ v \leftarrow w \]
\[ \text{while } v \text{ is labeled do} \]
\[ u \leftarrow \text{vertex indicated by } v\text{'s label}; \]
\[ M \leftarrow M - (v, u) \]
\[ v \leftarrow \text{vertex indicated by } u\text{'s label}; \]
\[ M \leftarrow M \cup (v, u) \]
\[ \text{remove all vertex labels} \]
\[ \text{reinitialize } Q \text{ with all free vertices in } V \]
\[ \textbf{break} \text{//exit the for loop} \]
\[ \text{else} \text{//} u \text{ is matched} \]
\[ \text{if } (w, u) \notin M \text{ and } u \text{ is unlabeled} \]
\[ \text{label } u \text{ with } w \]
\[ \text{Enqueue}(Q, u) \]
\[ \text{else} \text{//} w \in U \text{ (and matched)} \]
\[ \text{label the mate } v \text{ of } w \text{ with } “w} \]
\[ \text{Enqueue}(Q, v) \]
\[ \textbf{return } M \text{//current matching is maximum} \]
Notes on Maximum Matching Algorithm

Each iteration (except the last) matches two free vertices (one each from V and U). Therefore, the number of iterations cannot exceed \( \lceil n/2 \rceil + 1 \), where \( n \) is the number of vertices in the graph. The time spent on each iteration is in \( O(n+m) \), where \( m \) is the number of edges in the graph. Hence, the time efficiency is in \( O(n(n+m)) \).

This can be improved to \( O(\sqrt{n}(n+m)) \) by combining multiple iterations to maximize the number of edges added to matching \( M \) in each search.

Finding a maximum matching in an arbitrary graph is much more difficult, but the problem was solved in 1965 by Jack Edmonds.
Add a source and a sink, direct edges (with unit capacity) from the source to the vertices of $V$ and from the vertices of $U$ to the sink.

Direct all edges from $V$ to $U$ with unit capacity.
Stable Marriage Problem

There is a set $Y = \{m_1, \ldots, m_n\}$ of $n$ men and a set $X = \{w_1, \ldots, w_n\}$ of $n$ women. Each man has a ranking list of the women, and each woman has a ranking list of the men (with no ties in these lists).

A marriage matching $M$ is a set of $n$ pairs $(m_i, w_j)$. A pair $(m, w)$ is said to be a blocking pair for matching $M$ if man $m$ and woman $w$ are not matched in $M$ but prefer each other to their mates in $M$.

A marriage matching $M$ is called stable if there is no blocking pair for it; otherwise, it’s called unstable. The stable marriage problem is to find a stable marriage matching for men’s and women’s given preferences.
An instance of the stable marriage problem can be specified either by two sets of preference lists or by a ranking matrix, as in the example below.

<table>
<thead>
<tr>
<th>men’s preferences</th>
<th>women’s preferences</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st 2nd 3rd</td>
<td>1st 2nd 3rd</td>
</tr>
<tr>
<td>Bob: Lea Ann Sue</td>
<td>Ann: Jim Tom Bob</td>
</tr>
<tr>
<td>Jim: Lea Sue Ann</td>
<td>Lea: Tom Bob Jim</td>
</tr>
<tr>
<td>Tom: Sue Lea Ann</td>
<td>Sue: Jim Tom Bob</td>
</tr>
</tbody>
</table>

ranking matrix
Ann Lea Sue
Bob 2,3 1,2 3,3
Jim 3,1 1,3 2,1
Tom 3,2 2,1 1,2

{(Bob, Ann) (Jim, Lea) (Tom, Sue)} is unstable
{(Bob, Ann) (Jim, Sue) (Tom, Lea)} is stable
Stable Marriage Algorithm (Gale-Shapley)

Step 0  Start with all the men and women being free

Step 1 While there are free men, arbitrarily select one of them and do the following:

Proposal The selected free man $m$ proposes to $w$, the next woman on his preference list

Response If $w$ is free, she accepts the proposal to be matched with $m$. If she is not free, she compares $m$ with her current mate. If she prefers $m$ to him, she accepts $m$’s proposal, making her former mate free; otherwise, she simply rejects $m$’s proposal, leaving $m$ free

Step 2  Return the set of $n$ matched pairs
**Example**

<table>
<thead>
<tr>
<th></th>
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<th>Lea</th>
<th>Sue</th>
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<tbody>
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Bob proposed to Lea
Lea accepted

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Jim proposed to Lea
Lea rejected
### Example (cont.)

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Jim proposed to Sue Sue accepted

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Tom proposed to Sue Sue rejected
### Example (cont.)

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- Tom proposed to Lea. Lea replaced Bob with Tom.

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- Bob proposed to Ann. Ann accepted.

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*Getmynotes.com*
Analysis of the Gale-Shapley Algorithm

The algorithm terminates after no more than $n^2$ iterations with a stable marriage output.

The stable matching produced by the algorithm is always *man-optimal*: each man gets the highest rank woman on his list under any stable marriage. One can obtain the *woman-optimal* matching by making women propose to men.

A man (woman) optimal matching is unique for a given set of participant preferences.

The stable marriage problem has practical applications such as matching medical-school graduates with hospitals for residency training.