DM534 - Introduction to Computer Science, Week 48

## Graph Theory

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## Graph Theory - Motivation



## GRAPH THEORY: KEY TO UNDERSTANDING BIG DATA



## Social Networks



This graph might depict Facebook friendship relations, or Twitter follower relations, or...

## Chemical Compounds



## Metabolic Networks



Metabolic Network of E. coli.

## What is a graph?



Vertices:

## Edges:

Degree of a vertex:

P, Q, R, S, T all the lines
number of edges with that vertex as an end-point

## Interpretation:



The graph from the last slide might depict this roadmap. Note that the intersection of the lines PS and QT is not a vertex, since it does not correspond to a cross-roads

## Another Interpretation:



If $P, Q, R, S$ and $T$ represent football teams, then the existence of an edge might correspond to the playing of a game between the teams at its end-points. Thus, team $P$ has played against teams $Q, S$ and $T$, but not against team $R$. In this representation, the degree of vertex is the number of games played by the corresponding team.

## Two different graphs? No!



In the right graph we have removed the 'crossing' of the lines PS and QT by drawing the line PS outside the rectangle PQST. The resulting graph still tells us whether there is a direct road from one intersection to another, and which football teams have played which. The only information we have lost concerns 'metrical' properties, such as the length of a road and the straightness of a wire.

The first scientific article using the term graph


## Directed Graphs (Digraphs)



Assume again a graph depicts a roadmap. The study of directed graphs (or digraphs, as we abbreviate them) arises when making the roads into one-way streets. An example of a digraph is given above, the directions of the one-way streets being indicated by arrows. (In this example, there would be chaos at $T$, but that does not stop us from studying such situations!)

## Walks, Paths, and Cycles



Much of graph theory involves 'walks' of various kinds. A walk is a 'way of getting from one vertex to another', and consists of a sequence of edges, one following after another. For example, in the above figure $P \rightarrow Q \rightarrow P$ is a walk of length 2 , and $P \rightarrow S \rightarrow Q \rightarrow T \rightarrow S \rightarrow R$ is a walk of length 5 . A walk in which no vertex appears more than once is called a path; for example and $P \rightarrow Q \rightarrow R \rightarrow S$ is a path. A walk in which you end where you started, for example $Q \rightarrow S \rightarrow T \rightarrow Q$, is called a cycle.

## Connectedness



Some graphs are in two or more parts. For example, consider the graph whose vertices are the stations of the Copenhagen Metro and the New York Subway, and whose edges are the lines joining them. It is impossible to travel from $\emptyset$ sterport to Grand Central Station using only edges of this graph, but if we confine our attention to the Copenhagen Metro only, then we can travel from any station to any other. A graph that is in one piece, so that any two vertices are connected by a path, is a connected graph; a graph in more than one piece is a disconnected graph.

## Weighted Graphs



Consider the above graph: it is a connected graph in which a non-negative number is assigned to each edge. Such a graph is called a weighted graph, and the number assigned to each edge $e$ is the weight of $e$, denoted by $w(e)$.
Example: Suppose that we have a 'map' of the form shown above, in which the letters $A$ to $L$ refer to towns that are connected by roads. Then the weights may denote the length of these roads.

## Shortest Path (between one pair of vertices)



What is the length of the shortest path (=distance) from $A$ to $L$ ?
The problem is to find a path from A to L with minimum total weight. This problem is called the Shortest Path Problem. Note that, if we have a weighted graph in which each edge has weight 1 , then the problem reduces to that of finding the number of edges in the shortest path from $A$ to $L$.

## All-Pairs Shortest Path



What is the length of the shortest path (=distances) from any vertex to any vertex?
This problem is called the All-Pairs Shortest Path Problem

## All-Pairs Shortest Path : A Solution for Some Cities in Australia



DISTANCE IN KILOMETRES TO HOBART EXCLUDES MELBOURNE / DEVONPORT FERRY

One of the most decorative tables of distances (in Roman miles) between major European cities printed in the eighteenth century. Not only were the data extremely useful for traveling but also for sending a letter, because distance, not weight, determined the price.
(From the "Historic Maps Collection", Princeton University Library, link: here

## Matrix Representations for Graphs



$$
A=\left(\begin{array}{llll}
0 & 1 & 0 & 1 \\
1 & 0 & 1 & 2 \\
0 & 1 & 0 & 1 \\
1 & 2 & 1 & 0
\end{array}\right)
$$

$$
\mathbf{M}=\left(\begin{array}{llllll}
1 & 0 & 0 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 & 1 & 1 \\
0 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1
\end{array}\right)
$$

If $G$ is a graph with vertices labelled $\{1,2, \ldots\}$, its adjacency matrix $\mathbf{A}$ is the $n \times n$ matrix whose ij -th entry is the number of edges joining vertex $\boldsymbol{i}$ and vertex $\boldsymbol{j}$. Two nodes $\boldsymbol{i}$ and $\boldsymbol{j}$ are adjacent if the ij -th entry in the adjcacency matrix is larger than 0 .

If, in addition to the vertices, the edges are labelled $\{1,2, \ldots, m\}$, its incidence matrix $\mathbf{M}$ is the $n \times m$ matrix whose $i j$-th entry is 1 if vertex $\boldsymbol{i}$ is incident to edge $\boldsymbol{j}$ and 0 otherwise. The figure above shows a labelled graph $G$ with its adjacency and incidence matrices.

## Adjacency Matrix for Weighted Graphs



$$
\mathbf{A}=\left(\begin{array}{llll}
0 & 1 & 0 & 1 \\
1 & 0 & 1 & 2 \\
0 & 1 & 0 & 1 \\
1 & 2 & 1 & 0
\end{array}\right) \quad \mathbf{M}=\left(\begin{array}{llllll}
1 & 0 & 0 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 & 1 & 1 \\
0 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 1 & 1
\end{array}\right)
$$

Given a weighted graph $G$, the adjacency matrix $\mathbf{A}$ is the matrix whose ij -th entry is the weight of the edge between vertex $\boldsymbol{i}$ and vertex $\boldsymbol{j}$.

Matrix-Matrix Multiplication
Recap
$\left(\begin{array}{cccc}1 & 0 & 2 & 3 \\ -1 & 2 & 2 & 1\end{array}\right) \times\left(\begin{array}{ccc}1 & 2 & 3 \\ 4 & 5 & 2 \\ 1 & 2 & 1 \\ 1 & 2 & 5\end{array}\right)=($

## Matrix-Matrix Multiplication

## Recap

$$
\left(\begin{array}{cccc}
1 & 0 & 2 & 3 \\
-1 & 2 & 2 & 1
\end{array}\right) \times\left(\begin{array}{ccc}
1 & 2 & 3 \\
4 & 5 & 2 \\
1 & 2 & 1 \\
1 & 2 & 5
\end{array}\right)=(
$$

Matrix-Matrix Multiplication
Recap

$$
\begin{gathered}
\left(\begin{array}{cccc}
1 & 0 & 2 & 3 \\
-1 & 2 & 2 & 1
\end{array}\right) \times\left(\begin{array}{lll}
1 & 2 & 3 \\
4 & 5 & 2 \\
1 & 2 & 1 \\
1 & 2 & 5
\end{array}\right)=\left(\begin{array}{ccc}
6 & 12 & 20 \\
10 & 14 & 8
\end{array}\right) \\
M \times N=R \\
r_{i j}=\sum_{k} m_{i k} * n_{k j}
\end{gathered}
$$

## Matrix-Matrix Multiplication <br> Recap

$$
\left(\begin{array}{cccc}
1 & 0 & 2 & 3 \\
-1 & 2 & 2 & 1
\end{array}\right) \times\left(\begin{array}{ccc}
1 & 2 & 3 \\
4 & 5 & 2 \\
1 & 2 & 1 \\
1 & 2 & 5
\end{array}\right)=\left(\begin{array}{ccc}
6 & 12 & 20 \\
10 & 14 & 8
\end{array}\right)
$$

Zero-based Numbering ("Zero indexed")
$\left(\begin{array}{lll}r_{00} & r_{01} & r_{02} \\ r_{10} & r_{11} & r_{12}\end{array}\right)$

One-based Numbering ("One indexed")

$$
\left(\begin{array}{lll}
r_{11} & r_{12} & r_{13} \\
r_{21} & r_{22} & r_{23}
\end{array}\right)
$$

## Zero-Indexing

Zero-based numbering is a way of numbering in which the initial element of a sequence is assigned the index 0 , rather than the index 1 as is typical in everyday non-mathematical/non-programming circumstances.

Make sure that it is clear what you mean, when you say, e.g., the "row with index 1 " in a matrix.


## Matrix-Matrix Multiplication in Python (for Square Matrices)

```
# Assume M and N are both square (size x size) matrices
def multSquareMatrices(M,N):
    size = len(M)
    result = [[0 for x in range(size)] for y in range(size)]
    for i in range(size):
    for j in range(size):
            for k in range(size):
                result[i][j] = result[i][j] + M[i][k] * N[k][j]
```

return result
Provided Code: matMult.py

| Number of additions per result [i] [j] entry: | size |
| :--- | :--- |
| Number of multiplications per result [i] [j]entry: | size |
| Number of entries in the result matrix: | sizex size |
| Overall number of operations (additions and multiplications): | $2 \times$ size x ( sizex size ) |
|  | $\mathcal{O}\left(\operatorname{size}^{3}\right)$ |

## Matrix-Matrix Multiplication in Python

```
# Assume two matrices M and N, not necessarily squared
# (not needed further on in the lecture)
def multGeneral(M,N):
result = [[0 for x in range(len(N[0]))] for y in range(len(M))]
for i in range(len(M)):
    for j in range(len(N[0])):
        for k in range(len(N)):
            result[i][j] = result[i][j] + M[i][k] * N[k][j]
return result
```

Provided Code: matMult.py

## Comments to Python Code

- Creating a list of three 0's :

```
In [8]: [0 for i in range(3)]
Out [8]: [0, 0, 0]
```

- Creating a list of two lists with three 0's (i.e., a "matrix" of size $2 \times 3$ ):

```
In [8]: [0 for i in range(3)]
Out[8]: [0, 0, 0]
In [9]: [[0 for i in range(3)] for j in range(2)]
Out[9]: [[0, 0, 0], [0, 0, 0]]
```

$$
\left.M=\begin{array}{ccc}
{[[1,} & 0, & 2,
\end{array}\right],
$$

## Matrices in Python: Implemented as Lists of Lists:

```
In [1]: M
Out[1]: [[1, 0, 2, 3], [-1, 2, 2, 1]]
In [2]: N
Out[2]: [[1, 2, 3], [4, 5, 2], [1, 2, 1], [1, 2, 5]]
In [3]: S
Out[3]: [[1, 2, 0], [2, 0, 1], [-1, 2, 3]]
In [4]: multSquareMatrices(S,S)
Out[4]: [[5, 2, 2], [1, 6, 3], [0, 4, 11]]
In [5]: 
```

$N=[[1,2,3]$,
[4, 5, 2],
$[1,2,1]$,
$[1,2,5]]$
$S=[[1,2,0]$,
$[2,0,1]$,
$[-1,2,3]]$
print("Initial Matrix M:\n")
printMatrix(M)
print("Initial Matrix N:\n")
printMatrix(N)
print("M x N: \n")
printMatrix( multGeneral( $(\mathrm{M}, \mathrm{N})$ )
"Matrix" dimensions:

$A^{k}=\underbrace{A \times A \ldots \times A}_{k \text { times }}$ is called the k-th power of the adjacency matrix

## Theorem:

If $G$ is a graph with adjacency matrix $A$, and vertices with indices $1, \ldots, n$ then for each positive integer $k$

> the $i j$-th entry of $A^{k}$ is
the number of different walks using exactly $k$ edges from node $i$ to node $j$
$\left.A^{2}=\begin{array}{c}1 \\ 1 \\ 2 \\ 2 \\ 3 \\ 4 \\ 4 \\ 5 \\ 6\end{array}\left(\begin{array}{cccccc}2 & 3 & 4 & 5 & 6 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1\end{array}\right) \quad A^{3}=\begin{array}{c}1 \\ 2 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 6\end{array}\left(\begin{array}{cccccc}1 & 2 & 3 & 4 & 5 & 6 \\ 2 & 4 & 1 & 1 & 4 & 1 \\ 4 & 2 & 3 & 1 & 5 & 1 \\ 1 & 3 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 4 & 2 \\ 4 & 5 & 1 & 4 & 2 & 0 \\ 1 & 1 & 0 & 2 & 0 & 0\end{array}\right) \quad A^{4}=\begin{array}{cccccc}1 & 2 & 3 & 4 & 5 & 6 \\ 1 \\ 2 \\ 3 \\ 8 & 7 & 4 & 5 & 7 & 1 \\ 7 & 12 & 2 & 6 & 7 & 1 \\ 4 & 2 & 3 & 1 & 5 & 1 \\ 5 & 6 & 1 & 6 & 2 & 0 \\ 7 & 7 & 5 & 2 & 13 & 4 \\ 6 \\ 1 & 1 & 1 & 0 & 4 & 23\end{array}\right)$


## Example:

Consider the two vertices with index 4 and 5 in $A^{4}$

Length 4 walks:

1) 4 -> 5 -> 1 -> 2 -> 5
2) 4 -> 5 -> 2 -> $1->5$

There are 2 walks of length 4.
Furthermore, $A_{45}^{4}=2$.


## In Python3

```
def printMatrix(M):
    for row in M:
        print(["%3.0f" % a for a in row])
    print("\n")
```


$A=[[0,1,0,0,1,0]$, [1,0,1,0,1,0], [0,1,0,0,0,0], [0,0,0,0,1,1], [1,1,0,1,0,0], [0,0,0,1,0,0]]
\# make a copy of $X$
$R=\operatorname{deepcopy}(A)$
print("Initial Matrix:\n")
printMatrix(A)
for $i$ in range(2,5):
print("\%d-th power of A : \n"\%i)
$\mathrm{R}=$ multSquareMatrices $(\mathrm{R}, \mathrm{A})$
printMatrix(R)

Eule:IntroCS2017 daniel\$ ipython adjacencyMatMult.py
Initial Matrix:
Initial Matrix:



3-th power of A



## Proof: (also on blackboard)

Let $G$ be a graph with adjacency matrix $A$, and vertices $1, \ldots, n$. We proceed by induction on $k$ to obtain the result.

## Base Case:

Let $k=1 . A^{1}=A . a_{i j}$ is the number of edges from $i$ to $j$, which is identical to the number of walks of length 1 from $i$ to $j$.

## Inductive Step:

Assume true for a positive integer $k$. Let $b_{i j}$ be the $i j$-th entry of $A^{k}$, and let $a_{i j}$ be the $i j$-th entry of $A$. By the inductive hypothesis $b_{i j}$ is the number of walks of length $k$ from $i$ to $j$. Consider the $i j$-th entry of $A^{k+1}=A \times A^{k}$, i.e, $A_{i j}^{k+1}=a_{i 1} b_{1 j}+a_{i 2} b_{2 j}+\ldots+a_{i n} b_{n j}=\sum_{k=1}^{n} a_{i k} b_{k j}$. Consider $a_{i 1} b_{1 j}$. This is equal to the number of walks of length 1 from $i$ to 1 times the number of walks of length $k$ from 1 to $j$. This is therefor equal to the number of walks of length $k+1$ from $i$ to $j$, where 1 is the second vertex. This argument holds for each vertex $m$, i.e., $a_{i m} b_{m j}$ is the number of walks from $i$ to $j$ in which $m$ is the second vertex. Therefore, the sum is the number of all possible walks from $i$ to $j$.

## Algorithm for All-Pairs Shortest Path

Weighted Graph G with weights on edges:

- What is the distance (=length of the shortest path) between A and L ?


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Generalization:

- What are the distances of ALL paths (=lenghts of ALL shortest paths) between all pairs of nodes?
... and how can we find all these distances?



## The Edge Weight Matrix W

$$
W=\begin{gathered}
1 \\
1 \\
2 \\
3 \\
4 \\
5 \\
6
\end{gathered}\left(\begin{array}{cccccc}
1 & 2 & 3 & 4 & 5 & 6 \\
0 & 1 & \infty & \infty & 2 & \infty \\
1 & 0 & 2 & \infty & 4 & \infty \\
\infty & 2 & 0 & \infty & \infty & 3 \\
\infty & \infty & \infty & 0 & 6 & 1 \\
2 & 4 & \infty & 6 & 0 & \infty \\
\infty & \infty & 3 & 1 & \infty & 0
\end{array}\right)
$$


weights are depicted in red

Definition:
$W_{i j}= \begin{cases}\text { the weight of the edge }(i, j) & \text { if the edge }(i, j) \text { exists } \\ 0 & \text { if } i=j \\ \infty & \text { else }\end{cases}$
Interpretation:
$W_{i j}$ is the distance from vertex $i$ to vertex $j$ using maximally 1 edge

## Note: Matrix W has entries

 corresponding to infinity, as it might be impossible to reach vertex $j$ from vertex i via 1 edge.We assume all weights are not negative, i.e., larger or equal to 0.

## A modified Matrix-Matrix Multiplication

$$
\left(\begin{array}{lll}
1 & 0 & 2 \\
1 & 2 & 4 \\
3 & 1 & 2
\end{array}\right) \odot\left(\begin{array}{lll}
1 & 2 & 3 \\
4 & 5 & 2 \\
1 & 2 & 5
\end{array}\right)=\left(\begin{array}{lll}
2 & 3 & 2 \\
2 & 3 & 4 \\
3 & 4 & 3
\end{array}\right)
$$

$$
M \odot N=R
$$

## Definition:

$$
r_{i j}=\min _{k}\left\{m_{i k}+n_{k j}\right\}
$$

Example:

$$
\overline{r_{33}=\min }\{3+3,1+2,2+5\}=3
$$

Note: this operation is very similar to the standard matrix-matrix multiplication: however, for computation of the ij-th entry the multiplication is replaced by addition, and addition is replaced by the minimum operation.

## Theorem:

If $G$ is a weighted graph with edge weight matrix $W$, and vertices with indices $1, \ldots, n$ then for each positive integer $k$

$$
\text { the } i j \text {-th entry of } W^{k}=\underbrace{W \odot W \odot \ldots \odot W}_{k \text { times }}
$$

the length of the shortest path from $i$ to $j$ using maximally $k$ edges


## Examples:

Consider the two vertices with index 4 and 1 in $W^{4}$ Shortest Path using maximally 4 edges:
4 -> 6 -> 3 -> 2 -> 1 (distance 7)

Consider the two vertices with index 5 and 3 in $W^{4}$ Shortest Path using maximally 4 edges:
5 -> 1 -> 2 -> 3 (distance 5)
$\left.W^{2}=\begin{array}{c}1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6\end{array}\left(\begin{array}{cccccc}1 & 2 & 3 & 4 & 5 & 6 \\ 0 & 1 & 3 & 8 & 2 & \infty \\ 1 & 0 & 2 & 10 & 3 & 5 \\ 3 & 2 & 0 & 4 & 6 & 3 \\ 8 & 10 & 4 & 0 & 6 & 1 \\ 2 & 3 & 6 & 6 & 0 & 7 \\ \infty & 5 & 3 & 1 & 7 & 0\end{array}\right) \quad W^{3}=\begin{array}{c}1 \\ 2\end{array}\right)\left(\begin{array}{cccccc}1 \\ 2 & 1 & 3 & 8 & 2 & 6 \\ 2 & 0 & 2 & 6 & 3 & 5 \\ 4 \\ 3 & 2 & 0 & 4 & 5 & 3 \\ 8 & 6 & 4 & 0 & 6 & 1 \\ 2 & 3 & 5 & 6 & 0 & 7 \\ 6 & 5 & 3 & 1 & 7 & 0\end{array}\right)$

$W^{4}=$| 1 |
| :---: |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |\(\left(\begin{array}{cccccc}1 \& 2 \& 3 \& 4 \& 5 \& 6 <br>

0 \& 1 \& 3 \& 7 \& 2 \& 6 <br>
1 \& 0 \& 2 \& 6 \& 3 \& 5 <br>
3 \& 2 \& 0 \& 4 \& 5 \& 3 <br>
7 \& 6 \& 4 \& 0 \& 6 \& 1 <br>
2 \& 3 \& 5 \& 6 \& 0 \& 7 <br>
6 \& 5 \& 3 \& 1 \& 7 \& 0\end{array}\right)\)

## Matrix-Matrix Multiplication in Python (for Square Matrices)

```
# Assume M and N are both square (size x size) matrices
def multSquareMatrices(M,N):
    size = len(M)
    result = [[0 for x in range(size)] for y in range(size)]
    for i in range(size):
        for j in range(size):
            for k in range(size):
                result[i][j] = result[i][j] + M[i][k] * N[k][j]
```

    return result
    
## Modified Matrix-Matrix Multiplication in Python (for Square Matrices)

```
def multModSquareMatrices(M,N):
    size = len(M)
    result = [[inf for x in range(size)] for y in range(size)]
    for i in range(size):
        for j in range(size):
            for k in range(size):
                result[i][j] = min(result[i][j],M[i][k] +N[k][j])
    return result
```

Standard Matrix-
Matrix Multiplication:
\# Assume $M$ and $N$ are both square (size x size) matrices
def multSquareMatrices(M,N):
size = len(M)
result $=[[0$ for $x$ in range(size)] for $y$ in range(size)]
for $i$ in range(size):
for $j$ in range(size):
for $k$ in range(size):


## In Python3

```
W = [[ 0, 1, inf, inf, 2, inf],
    [ 1, 0, 2, inf, 4, inf],
    [inf, 2, 0, inf, inf, 3],
    [ inf, inf, inf, 0, 6, 1],
    [ 2, 4, inf, 6, 0, inf],
    [ 2, 4, inf, 6, 0, inf],
# make a copy of X
R = deepcopy(W)
print("Initial Matrix:\n")
printMatrix(W)
for i in range(2,5):
    print("%d-th power of W : \n"%i)
    R = multModSquareMatrices(R,W)
    printMatrix(R)
```

Eule:IntroCS2017 daniel\$ python3 shortestPaths.py
Initial Matrix:




$$
W \neq W^{2} \neq W^{3} \neq W^{4}=W^{5}=W^{6}=\ldots
$$

Which value of $k$ is necessary, in order to have $W^{k}$ contain all the pairwise distances of all vertexes?

## Answer: $n-1$ (which is identical to $|V|-1$ )

Assume all edge weights are not negative. The number of edges needed for a shortest path can maximally be $\mathrm{n}-1$, where n is the number of vertices in the graph. If the path would go via n edges, then you would have to visit at least one vertex twice, but then the path cannot be a shortest path anymore. Obviously $W^{k}=W^{n-1}$ for all $\mathrm{k}>\mathrm{n}-1$.


Lemma:
If $G$ is a weighted graph with edge weight matrix $W$, and vertices with indices $1, \ldots, n$ then

$$
\begin{gathered}
\text { the } i j \text {-th entry of } W^{n-1}=\underbrace{W \odot W}_{n-1 \text { times }} \\
\text { is } \\
\text { the distance from } i \text { to } j
\end{gathered}
$$

$D:=W^{n-1}$ is called the distance matrix of the graph G.

## Computation of the Distance Matrix by Repeated Squaring


n -2 matrix-matrix multiplication are needed in order to compute the distance matrix $D=W^{n-1}$

k matrix-matrix multiplication are needed (namely squaring a matrix $k$ times) in order to compute the matrix $W^{\left(2^{k}\right)}$
$2^{k}$ has to be larger or equal to $n-1$, or equivalently, k has to be larger or equal to $\log _{2}(n-1)$

Example: Consider a graph $G$ with 101 vertices. In order to compute the distance matrix $\mathrm{D}=W^{100}$, the left approach needs to make 99 matrix-matrix multiplications. The right approach (called repeated squaring) requires only 7 matrix-matrix multiplications, as $2^{7}=128$, and $\mathrm{D}=W^{128}=W^{100}$

## Test in Python3

```
# make a random edge weight matrix of size x size
size=100
W = [[0 for x in range(size)] for y in range(size)]
for i in range(size):
    for j in range(i,size):
        r = randint(0,10)
        W[i][j] = r
        W[j][i] = r
# make a copy of the edge weight matrix W
R = deepcopy(W)
print("Comparing runtimes for distance matrix computation for matrices of size %d x %d"%(size,size))
# find the distance matrix by (n-2) subsequent matrix matrix multiplications
# R = (((W*W)*W)*...*W) = W^(n-1)
t1 = time()
for i in range(0,size-2):
    R = multModSquareMatrices(R,W)
print("The n-2 multiplications for computing D took %3.2f seconds"%(time()-t1))
```

```
% set the R=W (re-initialize)
```

% set the R=W (re-initialize)
R deepcopy(W)

# find the distance matrix by ceil(log_2(n-1)) subsequent matrix matrix mulitplications via repeated squaring

# R = (((W^2)^2)^2...)^2

t1 = time()
for i in range(0, ceil(log2(size-1))):
R = multModSquareMatrices(R,R)
print("The ceil(log_2(n-1)) multiplications took %3.2f seconds"%(time()-t1))

```
Note: ceil(log2 (size-1)) returns
the smallest integer larger or equal to
\(\log 2\) ( size-1), i.e., R will be the
distance matrix after this for loop.
```

Eule:IntroCS2017 daniel\$ python3 timing.py
Comparing runtimes for distance matrix computation for matrices of size $100 \times 100$
The n-2 multiplications for computing D took 40.27 seconds
The ceil(log_2(n-1)) multiplications took 2.93 seconds
Eule:IntroCS2017 daniel\$

```

The most obvious Application of Computing the Distance Matrix:


\section*{Another Application of the Distance Matrix: Predicting Boiling Points of Paraffins}

In 1947 Harry Wiener defined the Wiener-Index of a graph G in order to predict the boiling point of different paraffins. He used the graph representation \(G\) of the carbon backbone of a molecule with \(n\) carbon atoms and calculated the WienerIndex the sum of all distances between all pairs of vertexes, i.e.
\[
\mathcal{W}(G)=\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} D_{i j}
\]

He predicted the boiling point \(t_{B}\) to be
\[
\begin{aligned}
t_{B} & =t_{0}-\left(\frac{98}{n^{2}}\left(w_{0}-\mathcal{W}(G)\right)+5.5 \cdot\left(p_{0}-p\right)\right) \\
\text { with } t_{0} & =745.42 \cdot \log _{10}(n+4.4)-689.4 \\
w_{0} & =\frac{1}{6} \cdot(n+1) \cdot n \cdot(n-1) \\
p_{0} & =n-3 \\
p & =\text { the number of shortest paths } i \rightarrow \ldots \rightarrow j \text { of length } 3 \text { in } G \text { with } i<j \\
& =\text { half of the number of entries " } 3 \text { " in the distance matrix } D
\end{aligned}
\]

\section*{Wiener Index: Boiling Point Prediction, Example (2,2-dimethylbutan)}


The carbon backbone


Graph G
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline & 1 & 2 & 3 & 4 & 5 & 6 \\
\hline \multirow{6}{*}{\(W=\)} & \((0\) & \(\infty\) & 1 & \(\infty\) & \(\infty\) & \(\infty\) \\
\hline & \(\infty\) & 0 & 1 & \(\infty\) & \(\infty\) & \(\infty\) \\
\hline & - & 1 & 0 & 1 & 1 & \(\infty\) \\
\hline & \(\infty\) & \(\infty\) & 1 & 0 & \(\infty\) & 1 \\
\hline & \(\infty\) & \(\infty\) & 1 & \(\infty\) & 0 & \(\infty\) \\
\hline & ( \(\infty\) & \(\infty\) & \(\infty\) & 1 & \(\infty\) & 0 \\
\hline
\end{tabular}

Edge Weight Matrix
Note: Depending on how you chose to label your graph, the edge weight matrix might look different. This won't matter for the subsequent calculations.
\[
\begin{aligned}
t_{B} & =t_{0}-\left(\frac{98}{n^{2}}\left(w_{0}-\mathcal{W}(G)\right)+5.5 \cdot\left(p_{0}-p\right)\right) \\
& =68.72-\frac{98}{36}(35-28)+5.5 \cdot(3-3) \\
& =49.66
\end{aligned}
\]

Calculation of Wiener Index and other parameters, as well as the resulting boiling point prediction.

\section*{Wiener Index: Boiling Point Prediction, Example (2,2-dimethylbutan)}


Predicted Boiling Point: \(t_{B}=49.66\)
Real Boiling Point: \(t_{B}^{\text {real }} \approx 49.7-50.0\)

The prediction of boiling points of paraffins based on the Wiener-Index of the corresponding molecular graph is amazingly accurate. Try it yourself (see exercises)! Intuitively, the Wiener-Index quantifies the "compactness" of a graph (or molecule). Long single chained molecules with \(n\) carbons have a smaller Wiener-Index than molecules that contain many branches. Long molecules are easier to break, and have usually a lower boiling point.
```

