Case Study: PageRank Algorithm
Outline

1. Random Surfer Model
2. Input Format
3. Transition Matrix
4. Simulating a Random Surfer
5. Markov Chain
Random Surfer Model

The random surfer model is a simple model of the world-wide web (www) that has proven to be a particularly useful approach to understand some of its properties.

The www is modeled as a fixed set of pages, with each page containing a fixed set of links (called hyperlinks), and each link is a reference to some other page; such an abstraction is called a graph in mathematics.

We are interested in what happens to a person (a random surfer) who randomly moves from page to page according to the 90-10 rule: 90% of the time the random surfer clicks a random link on the current page and 10% of the time the random surfer goes directly to a random page by typing a page name into the address bar.

Page rank is the probability that the random surfer lands on a page.
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Input Format

A tiny web of five pages

and a file tiny.txt that encodes it

$ more tiny.txt
5
0 1
1 2 1 2
1 3 1 3
1 4
2 3
3 0
4 0 4 2
Input Format

A tiny web of five pages

and a file tiny.txt that encodes it

$ more tiny.txt
5
0 1
1 2 1 2
1 3 1 3
1 4
2 3
3 0
4 0 4 2
Input Format

A tiny web of five pages

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```
$ more tiny.txt
5
0 1
1 2 1 2
1 3 1 3
1 4
2 3
3 0
4 0 4 2
```
The transition matrix $P$ for a www with $N$ pages is an $N$-by-$N$ matrix such that the entry $P_{ij}$, ie, the entry in row $i$ and column $j$, is the probability that the random surfer moves to page $j$ when on page $i$.

For example, a transition matrix for our tiny five-page web is

$$
P = \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}$$
The transition matrix $P$ for a www with $N$ pages is an $N$-by-$N$ matrix such that the entry $P_{ij}$, i.e., the entry in row $i$ and column $j$, is the probability that the random surfer moves to page $j$ when on page $i$.

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.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02 \\
\end{bmatrix}$$
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.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02 \\
\end{bmatrix}$$
transition.py: Read links from standard input and write the corresponding transition matrix to standard output. First, process the input to count the outlinks from each page. Then apply the 90-10 rule to compute the transition matrix. Assume that there are no pages that have no outlinks in the input.

```
import stdarray
import stdio

n = stdio.readInt()
linkCounts = stdarray.create2D(n, n, 0)
outDegrees = stdarray.create1D(n, 0)
while not stdio.isEmpty():
    i = stdio.readInt()
    j = stdio.readInt()
    outDegrees[i] += 1
    linkCounts[i][j] += 1
stdio.writeln(str(n) + ' ' + str(n))
for i in range(n):
    for j in range(n):
        p = (.90 * linkCounts[i][j] / outDegrees[i]) + (.10 / n)
        stdio.writef('%.5f', p)
stdio.writeln()
```

$ python3 transition.py < tiny.txt
5 5
0.02000 0.92000 0.02000 0.02000 0.02000
0.02000 0.02000 0.38000 0.38000 0.20000
0.02000 0.02000 0.02000 0.92000 0.02000
0.92000 0.02000 0.02000 0.02000 0.02000
0.47000 0.02000 0.47000 0.02000 0.02000
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    j = stdio.readInt()
    outDegrees[i] += 1
    linkCounts[i][j] += 1
stdio.writeln(str(n) + ' ' + str(n))
for i in range(n):
    for j in range(n):
        p = (0.90 * linkCounts[i][j] / outDegrees[i]) + (0.10 / n)
        stdio.writef('%.5f', p)
    stdio.writeln()
```

$ python3 transition.py < tiny.txt
5 5
0.02000 0.92000 0.02000 0.02000 0.02000
0.02000 0.02000 0.38000 0.38000 0.20000
0.02000 0.02000 0.02000 0.92000 0.02000
0.92000 0.02000 0.02000 0.02000 0.02000
0.47000 0.02000 0.47000 0.02000 0.02000
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    i = stdio.readInt()
    j = stdio.readInt()
    outDegrees[i] += 1
    linkCounts[i][j] += 1
stdio.writeln(str(n) + ' ' + str(n))
for i in range(n):
    for j in range(n):
        p = (.90 * linkCounts[i][j] / outDegrees[i]) + (.10 / n)
        stdio.writef('%8.5f', p)
stdio.writeln()
```

```
$ python3 transition.py < tiny.txt
5 5
 0.02000 0.92000 0.02000 0.02000 0.02000
 0.02000 0.02000 0.38000 0.38000 0.20000
 0.02000 0.02000 0.02000 0.92000 0.02000
 0.92000 0.02000 0.02000 0.02000 0.02000
 0.47000 0.02000 0.47000 0.02000 0.02000
```
Simulating a Random Surfer

`randomsurfer.py`: Accept an integer `moves` as a command-line argument. Read a transition matrix from standard input. Perform `moves` moves as prescribed by the transition matrix, and write to standard output the relative frequency of hitting each page, i.e., its page rank.

```python
import random
import stdarray
import stdio
import sys

moves = int(sys.argv[1])
n = stdio.readInt()
stdio.readInt()
p = stdarray.create2D(n, n, 0.0)
for i in range(n):
    for j in range(n):
        p[i][j] = stdio.readFloat()
hits = stdarray.create1D(n, 0)
page = 0
for i in range(moves):
    r = random.random()
total = 0.0
    for j in range(0, n):
        total += p[page][j]
    if r < total:
        page = j
        break
    hits[page] += 1
for v in hits:
    stdio.writef("%8.5f", 1.0 * v / moves)
stdio.writeln()
```
Simulating a Random Surfer

randomsurfer.py: Accept an integer moves as a command-line argument. Read a transition matrix from standard input. Perform moves moves as prescribed by the transition matrix, and write to standard output the relative frequency of hitting each page, i.e., its page rank.

```python
import random
import stdarray
import stdio
import sys

moves = int(sys.argv[1])
n = stdio.readInt()

p = stdarray.create2D(n, n, 0.0)
for i in range(n):
    for j in range(n):
        p[i][j] = stdio.readFloat()

hits = stdarray.create1D(n, 0)
page = 0
for i in range(moves):
    r = random.random()
    total = 0.0
    for j in range(0, n):
        total += p[page][j]
    if r < total:
        page = j
        break
    hits[page] += 1

for v in hits:
    stdio.writef("%.5f", 1.0 * v / moves)
stdio.writeln()
```

```text
pages
0 0.0 0.47 0.49 0.96 0.98 1.00
0.0 r = 0.71, page = 2
0.47 0.02 0.47 0.02 0.02
0.49
0.96
0.98
1.00
```

```
```
```
$ python3 transition.py < tiny.txt | python3 randomsurfer.py 100
 0.26000 0.27000 0.18000 0.26000 0.03000
$ python3 transition.py < tiny.txt | python3 randomsurfer.py 10000
 0.27410 0.26500 0.14570 0.24890 0.06630
$ python3 transition.py < tiny.txt | python3 randomsurfer.py 10000000
 0.27308 0.26568 0.14616 0.24719 0.06789
Simulating a Random Surfer

```
$ python3 transition.py < tiny.txt | python3 randomsurfer.py 100
 0.26000 0.27000 0.18000 0.26000 0.03000
$ python3 transition.py < tiny.txt | python3 randomsurfer.py 10000
 0.27410 0.26500 0.14570 0.24890 0.06630
$ python3 transition.py < tiny.txt | python3 randomsurfer.py 10000000
 0.27308 0.26568 0.14616 0.24719 0.06789
```
Markov Chain

A Markov chain is a random process that describes behavior similar to the random surfer.

An useful property of Markov chains is that of mixing, which states that the random surfer could start anywhere, since the probability that the surfer eventually winds up on any particular page is the same for all starting pages.

Using the power method we can obtain the probability $P^2_{ij}$ that the random surfer will move from page $i$ to page $j$ in two moves by squaring the transition matrix $P$:

$$P^2_{ij} = P_i \cdot P_{ij}$$

For example, for our tiny web, we have

$$P^2_{ij} = \begin{bmatrix} .02 & .92 & .02 & .02 & .02 \\ .02 & .02 & .38 & .38 & .20 \\ .02 & .02 & .02 & .92 & .02 \\ .92 & .02 & .02 & .02 & .02 \\ .47 & .02 & .47 & .02 & .02 \end{bmatrix} \cdot \begin{bmatrix} .02 & .92 & .02 & .02 & .02 \\ .02 & .02 & .38 & .38 & .20 \\ .02 & .02 & .02 & .92 & .02 \\ .92 & .02 & .02 & .02 & .02 \\ .47 & .02 & .47 & .02 & .02 \end{bmatrix}$$

$$= \begin{bmatrix} .05 & .04 & .36 & .37 & .19 \\ .45 & .04 & .12 & .37 & .02 \\ .86 & .04 & .04 & .05 & .02 \\ .05 & .85 & .04 & .05 & .02 \\ .05 & .44 & .04 & .45 & .02 \end{bmatrix}$$
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Using the power method we can obtain the probability $P_{ij}^2$ that the random surfer will move from page $i$ to page $j$ in two moves by squaring the transition matrix $P$:

$$P_{ij}^2 = P_i \cdot P_{ij}$$

For example, for our tiny web, we have

$$P_{ij}^2 = \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02 \\
\end{bmatrix} \cdot \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02 \\
\end{bmatrix}$$

$$= \begin{bmatrix}
.05 & .04 & .36 & .37 & .19 \\
.45 & .04 & .12 & .37 & .02 \\
.86 & .04 & .04 & .05 & .02 \\
.05 & .85 & .04 & .05 & .02 \\
.05 & .44 & .04 & .45 & .02 \\
\end{bmatrix}$$
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$$P_{ij}^2 = P_i \cdot P_{ij}$$

For example, for our tiny web, we have

$$P_{ij}^2 = \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix} \cdot \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}$$

$$= \begin{bmatrix}
.05 & .04 & .36 & .37 & .19 \\
.45 & .04 & .12 & .37 & .02 \\
.86 & .04 & .04 & .05 & .02 \\
.05 & .85 & .04 & .05 & .02 \\
.05 & .44 & .04 & .45 & .02
\end{bmatrix}$$
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Using the power method we can obtain the probability $P_{ij}^2$ that the random surfer will move from page $i$ to page $j$ in two moves by squaring the transition matrix $P$:

$$P_{ij}^2 = P_i \cdot P_{:j}$$

For example, for our tiny web, we have:

$$P_{ij}^2 = \begin{bmatrix} .02 & .92 & .02 & .02 & .02 \\ .02 & .02 & .38 & .38 & .20 \\ .02 & .02 & .02 & .92 & .02 \\ .92 & .02 & .02 & .02 & .02 \\ .47 & .02 & .47 & .02 & .02 \end{bmatrix} \cdot \begin{bmatrix} .02 & .92 & .02 & .02 & .02 \\ .02 & .02 & .38 & .38 & .20 \\ .02 & .02 & .02 & .92 & .02 \\ .92 & .02 & .02 & .02 & .02 \\ .47 & .02 & .47 & .02 & .02 \end{bmatrix} = \begin{bmatrix} .05 & .04 & .36 & .37 & .19 \\ .45 & .04 & .12 & .37 & .02 \\ .86 & .04 & .04 & .05 & .02 \\ .05 & .85 & .04 & .05 & .02 \\ .05 & .44 & .04 & .45 & .02 \end{bmatrix}$$
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$$P_{ij}^2 = P_i \cdot P : j$$

For example, for our tiny web, we have

$$P_{ij}^2 = \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix} \cdot \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .02 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}$$

$$= \begin{bmatrix}
.05 & .04 & .36 & .37 & .19 \\
.45 & .04 & .12 & .37 & .02 \\
.86 & .04 & .04 & .05 & .02 \\
.05 & .85 & .04 & .05 & .02 \\
.05 & .44 & .04 & .45 & .02
\end{bmatrix}$$
Markov Chain

In general, the probability that the random surfer will move from page $i$ to page $j$ in $t$ moves is obtained by computing $P^t$.

Unfortunately, matrix-matrix multiplication is expensive.

Fortunately, because of the mixing property, we can make do with relatively inexpensive vector-matrix multiplications.

For example, with our tiny web, if we start with the vector

$$[1.0 \ 0.0 \ 0.0 \ 0.0 \ 0.0]$$

specifying that the random surfer starts on page 0, multiplying the vector by the transition matrix $P$ gives the vector

$$\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}
\begin{bmatrix}
1.0 \\
0.0 \\
0.0 \\
0.0 \\
0.0
\end{bmatrix} =
\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}$$

specifying the probabilities that the surfer winds up on each of the pages after one step.
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specifying the probabilities that the surfer winds up on each of the pages after one step
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In general, the probability that the random surfer will move from page $i$ to page $j$ in $t$ moves is obtained by computing $P^t$.

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$$ [1.0 \ 0.0 \ 0.0 \ 0.0 \ 0.0] $$

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$$
\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}
\begin{bmatrix}
1.0 \\
0.0 \\
0.0 \\
0.0 \\
0.0
\end{bmatrix}
= 
\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix}
$$

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$$\begin{bmatrix} .02 & .92 & .02 & .02 & .02 \\ .02 & .02 & .38 & .38 & .20 \\ .92 & .02 & .02 & .92 & .02 \\ .47 & .02 & .47 & .02 & .02 \end{bmatrix} \cdot \begin{bmatrix} 1.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{bmatrix} = \begin{bmatrix} .02 & .92 & .02 & .02 & .02 \end{bmatrix}$$

specifying the probabilities that the surfer winds up on each of the pages after one step.
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Fortunately, because of the mixing property, we can make do with relatively inexpensive vector-matrix multiplications.

For example, with our tiny web, if we start with the vector

$$[1.0 \ 0.0 \ 0.0 \ 0.0 \ 0.0]$$

specifying that the random surfer starts on page 0, multiplying the vector by the transition matrix $P$ gives the vector

$$[1.0 \ 0.0 \ 0.0 \ 0.0 \ 0.0] \cdot \begin{bmatrix} .02 & .92 & .02 & .02 & .02 \\ .02 & .02 & .38 & .38 & .20 \\ .92 & .02 & .02 & .92 & .02 \\ .47 & .02 & .47 & .02 & .02 \end{bmatrix} = [ .02 \ .92 \ .02 \ .02 \ .02 ]$$

specifying the probabilities that the surfer winds up on each of the pages after one step.
Now, multiplying the above vector by the transition matrix $P$ again gives the vector

$$
\begin{pmatrix}
0.02 & 0.92 & 0.02 & 0.02 & 0.02 \\
0.02 & 0.02 & 0.38 & 0.38 & 0.20 \\
0.92 & 0.02 & 0.02 & 0.92 & 0.02 \\
0.47 & 0.02 & 0.47 & 0.02 & 0.02 \\
\end{pmatrix}
\begin{pmatrix}
0.02 \\
0.02 \\
0.02 \\
0.02 \\
\end{pmatrix}
= 
\begin{pmatrix}
0.05 \\
0.04 \\
0.36 \\
0.37 \\
0.19 \\
\end{pmatrix}
$$

which contains the probabilities that the surfer winds up on each of the pages after two steps.

The vector giving the probabilities that the random surfer is at each page after $t$ steps is the product of the corresponding vector for $t-1$ steps and the transition matrix $P$. 
Now, multiplying the above vector by the transition matrix $P$ again gives the vector

$$
\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix} \cdot \begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .02 & .92 & .02 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02
\end{bmatrix} = \begin{bmatrix}
.05 & .04 & .36 & .37 & .19
\end{bmatrix}
$$

which contains the probabilities that the surfer winds up on each of the pages after two steps.

The vector giving the probabilities that the random surfer is at each page after $t$ steps is the product of the corresponding vector for $t - 1$ steps and the transition matrix $P$. 
Now, multiplying the above vector by the transition matrix \( P \) again gives the vector

\[
\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02 \\
\end{bmatrix} \cdot
\begin{bmatrix}
.02 & .92 & .02 & .02 & .02 \\
.02 & .02 & .38 & .38 & .20 \\
.92 & .02 & .02 & .92 & .02 \\
.47 & .02 & .47 & .02 & .02 \\
\end{bmatrix} = \begin{bmatrix}
.05 & .04 & .36 & .37 & .19 \\
\end{bmatrix}
\]

which contains the probabilities that the surfer winds up on each of the pages after two steps.

The vector giving the probabilities that the random surfer is at each page after \( t \) steps is the product of the corresponding vector for \( t - 1 \) steps and the transition matrix \( P \).
Markov Chain

markov.py: Accept integer moves from the command-line, and read a transition matrix from standard input. Compute the probabilities that a random surfer lands on each page (page ranks) after moves matrix-vector multiplications, and write the page ranks to standard output.

```python
import stdarray
import stdio
import sys

moves = int(sys.argv[1])
n = stdio.readInt()
stdio.readInt()
probs = stdarray.create2D(n, n, 0.0)
for i in range(n):
    for j in range(n):
        probs[i][j] = stdio.readFloat()

ranks = stdarray.create1D(n, 0.0)
ranks[0] = 1.0
for i in range(moves):
    newRanks = stdarray.create1D(n, 0.0)
    for j in range(n):
        for k in range(n):
            newRanks[j] += ranks[k] * probs[k][j]
    ranks = newRanks
for rank in ranks:
    stdio.writef("%8.5f", rank)
stdio.writeln()
```

$ python3 transition.py < tiny.txt | python3 markov.py 20
0.27245 0.26515 0.14669 0.24764 0.06806
$ python3 transition.py < tiny.txt | python3 markov.py 40
0.27303 0.26573 0.14618 0.24723 0.06783
Markov Chain

markov.py: Accept integer `moves` from the command-line, and read a transition matrix from standard input. Compute the probabilities that a random surfer lands on each page (page ranks) after `moves` matrix-vector multiplications, and write the page ranks to standard output.

```python
import stdarray
import stdio
import sys

moves = int(sys.argv[1])
n = stdio.readInt()
stdio.readInt()
probs = stdarray.create2D(n, n, 0.0)
for i in range(n):
    for j in range(n):
        probs[i][j] = stdio.readFloat()

ranks = stdarray.create1D(n, 0.0)
ranks[0] = 1.0
for i in range(moves):
    newRanks = stdarray.create1D(n, 0.0)
    for j in range(n):
        for k in range(n):
            newRanks[j] += ranks[k] * probs[k][j]

    ranks = newRanks
for rank in ranks:
    stdio.writef("%.5f", rank)
stdio.writeln()
```

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Markov Chain

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```

```
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```