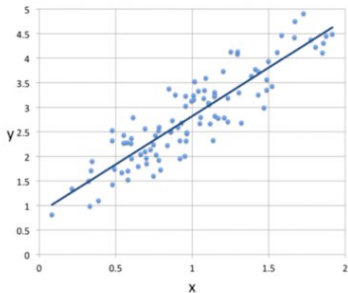


12

Chapter 6 : Orthogonality and Least Squares

6.6 : Applications to Linear Models



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Topics and Objectives

Topics

1. Least Squares Lines
2. Linear and more complicated models

Learning Objectives

For the topics covered in this section, students are expected to be able to do the following.

1. Apply least-squares and multiple regression to construct a linear model from a set of data points.
2. Apply least-squares to fit polynomials and other curves to data.

Motivating Question

Compute the equation of the line $y = \beta_0 + \beta_1 x$ that best fits the data

x	2	5	7	8
y	1	1	4	3

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8	2/26 - 3/1	5.2	WS5.1,5.2	Exam 2, Review	Cancelled	5.3
9	3/4 - 3/8	5.3	WS5.3	5.5	WS5.5	6.1
10	3/11 - 3/15	6.1,6.2	WS6.1	6.2	WS6.2	6.3
11	3/18 - 3/22	Break	Break	Break	Break	Break
12	3/25 - 3/29	6.4	WS6.3	6.4,6.5	WS6.4	6.5
13	4/1 - 4/5	6.6	WS6.5,6.6	Exam 3, Review	Cancelled	PageRank

Topics

1. Least Squares Lines
2. Linear and more complicated models

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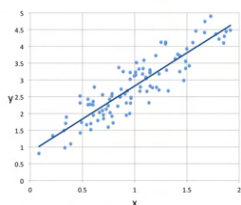
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y	1	1	4	3

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Chapter 6 : Orthogonality and Least Squares
6.6 : Applications to Linear Models



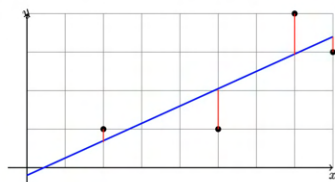
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The Least Squares Line

Graph below gives an approximate linear relationship between x and y .

1. Black circles are data.
2. Blue line is the **least squares line**.
3. Lengths of red lines are the **residuals**.

The least squares line minimizes the sum of squares of the residuals.



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Example 1 Compute the least squares line $y = \beta_0 + \beta_1 x$ that best fits the data

x	2	5	7	8
y	1	1	4	3

We want to solve

$$A^T \rightarrow \begin{bmatrix} 1 & 2 \\ 1 & 5 \\ 1 & 7 \\ 1 & 8 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 4 \\ 3 \end{bmatrix} \leftarrow b^T$$

This is a least-squares problem : $X\vec{\beta} = \vec{y}$.

Step 1 compute ATA , ATb

Step 2 Solve Normal eqns $ATAx = ATb$.

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Critical idea:

plug in data into model to get $Ax = b$ system of linear eqns

New idea: What if instead of model $y = \beta_0 + \beta_1 x$

we want ?

$$y = \beta_0 x^2 + \beta_1 x \quad ??$$

The normal equations are

$$X^T X = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 5 & 7 & 8 \end{bmatrix} = \begin{bmatrix} 4 & 22 \\ 22 & 142 \end{bmatrix}$$

$$X^T \vec{y} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 5 & 7 & 8 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 4 \\ 3 \end{bmatrix} = \begin{bmatrix} 9 \\ 59 \end{bmatrix}$$

So the least-squares solution is given by

$$\begin{bmatrix} 4 & 22 \\ 22 & 142 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 9 \\ 59 \end{bmatrix}$$

$$y = \beta_0 + \beta_1 x = -\frac{5}{21} + \frac{19}{42}x$$

As we may have guessed, β_0 is negative, and β_1 is positive.

Least Squares Fitting for Other Curves

We can consider least squares fitting for the form

$$y = \beta_0 + \beta_1 f_1(x) + \beta_2 f_2(x) + \dots + \beta_n f_n(x).$$

where the functions f_j are known. Should have only a few functions! Keep in mind this is a **linear problem in the β variables**.

$$y = \beta_0 x^2 + \beta_1 x$$

Example 1 Compute the least squares line $y = \beta_0 + \beta_1 x$ that best fits the data

x	2	5	7	8
y	1	1	4	3

We want to solve

new A

$$\begin{bmatrix} 1 & 2 \\ 1 & 5 \\ 1 & 7 \\ 1 & 8 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 4 \\ 3 \end{bmatrix}$$

This is a least-squares problem $\hat{\beta} = \hat{y}$.

new least for β_0

same least for β_1

So plug in data into model

$$y = \beta_0 x^2 + \beta_1 x$$

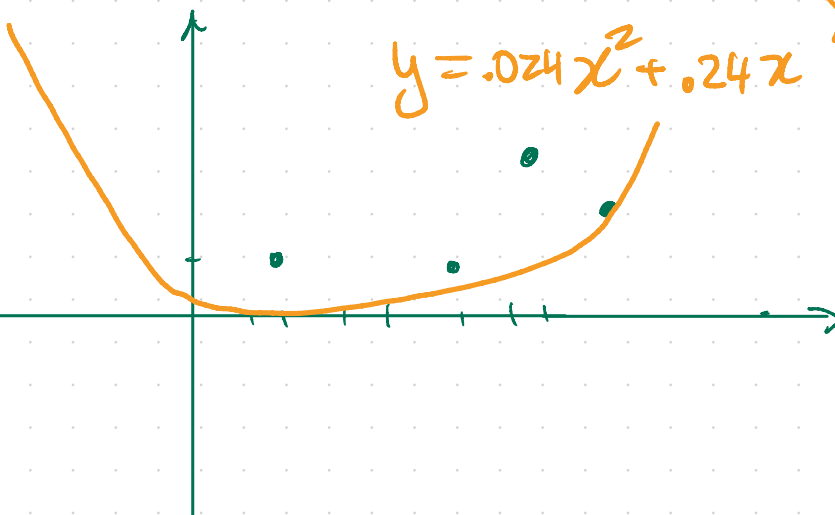
$$\begin{aligned} C(2,1) & \quad \beta_0(2)^2 + \beta_1(2) = 1 \\ C(5,1) & \quad \beta_0(5)^2 + \beta_1(5) = 1 \\ C(7,4) & \quad \beta_0(7)^2 + \beta_1(7) = 4 \\ C(8,3) & \quad \beta_0(8)^2 + \beta_1(8) = 3 \end{aligned}$$

$$\text{So } \begin{cases} 4\beta_0 + 2\beta_1 = 1 \\ 25\beta_0 + 5\beta_1 = 1 \\ 49\beta_0 + 7\beta_1 = 4 \\ 64\beta_0 + 8\beta_1 = 3 \end{cases}$$

$$A = \begin{bmatrix} 4 & 2 \\ 25 & 5 \\ 49 & 7 \\ 64 & 8 \end{bmatrix} \quad b = \begin{bmatrix} 1 \\ 1 \\ 4 \\ 3 \end{bmatrix}$$

Solve $ATA x = ATb$ to get $\hat{x} = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}$ LS-soln

$$y = .024x^2 + .24x \quad \hat{x} = \begin{pmatrix} .0246 \\ .2442 \end{pmatrix}$$



Model choices 2

① $y = \alpha + \beta x$

② $y = \alpha x + \beta x^2$

③ $y = \alpha_0 + \alpha_1 x + \alpha_2 x^2 + \alpha_3 x^3$

④ $y = a_1 x + a_2 x^2$

⑤ $y = \alpha x + \beta e^{x^2}$

⑥ $y = \alpha x + \beta \cos x$

data =

1	5
2	2
4	5
5	11
8	20

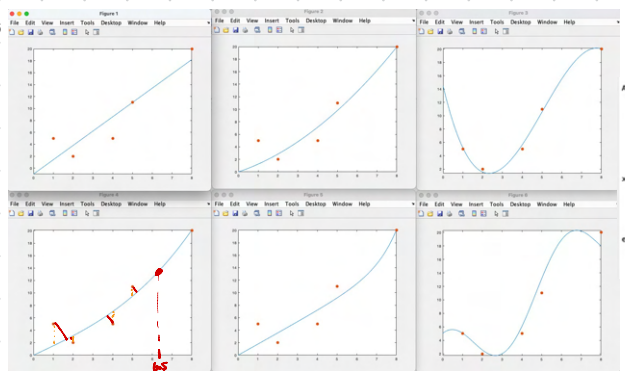
data =

1	8
2	3
4	8
5	11
8	20

data =

1	1
2	1
4	8
5	11
8	20

data
(1,5)
(2,2)
(4,5)
(5,11)
(8,20)



A =

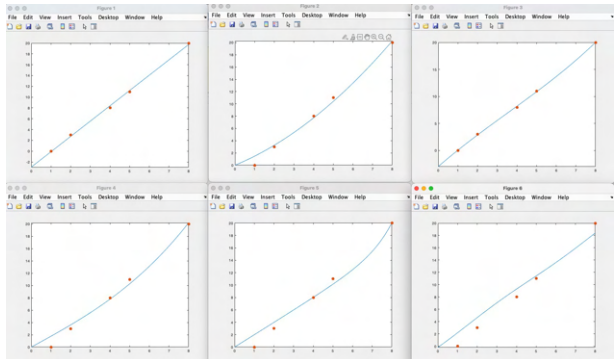
1	1
2	1
4	1
5	1
8	1

what =

2.4667
-1.8667

errorLine =

3.5824



A =

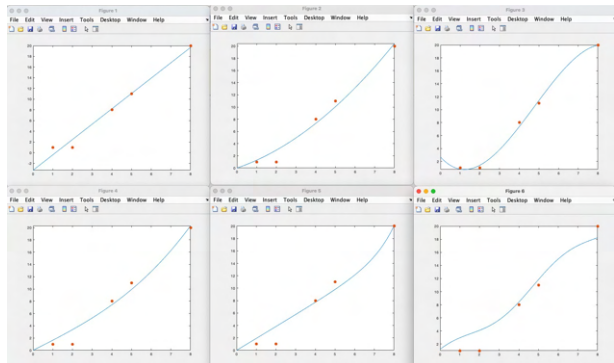
1	1
2	4
4	16
5	25
8	64

what =

1.3882
8.13765

errorQuad =

2.4685



A =

1	1
2	4
4	16
5	25
8	64

what =

1.3882
8.13765

errorCubic =

3.3015

data =	
1	5
2	2
4	2
5	11
8	20

data
(1,5)
(2,2)
(4,5)
(5,11)
(8,20)

linear $y = \alpha x + \beta$
 ① Model $y = \alpha + \beta x$
 system of linear eqns.

$@(1,5) \quad \alpha + \beta(1) = 5$
 $@(2,2) \quad \alpha + \beta(2) = 2$
 $@(4,5) \quad \alpha + \beta(4) = 5$
 $@(5,11) \quad \alpha + \beta(5) = 11$
 $@(8,20) \quad \alpha + \beta(8) = 20$

design matrix $A = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 4 \\ 1 & 5 \\ 1 & 8 \end{bmatrix}$ $\vec{b} = \begin{bmatrix} 5 \\ 2 \\ 5 \\ 11 \\ 20 \end{bmatrix}$ $\hat{x} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix}$

$\uparrow$ α -coeff $\uparrow$ β -coeff

Solve $A\vec{x} = \vec{b}$? inconsistent

Find a L-S soln to $A\vec{x} = \vec{b}$

How? $A^T A \hat{x} = A^T \vec{b}$

Normal eqns. solve these.

$A^T A$ invertible? yes:

$\hookrightarrow$ unique L-S soln to $A\vec{x} = \vec{b}$
 find unique soln to normal eqns.

$$\hat{x} = (A^T A)^{-1} A^T \vec{b} = \begin{bmatrix} 2.4 \\ -1 \end{bmatrix}$$

$\in \mathbb{R}$ $\neq \mathbb{C}$

So best linear model

$$y = 2.4x - 1$$

key idea
plug in
data into
Model

Model choices $\rightarrow$

① $y = \alpha + \beta x$ α, β

② $y = \alpha x + \beta x^2$

③ $y = a_0 + a_1 x + a_2 x^2 + a_3 x^3$

④ $y = a_1 x + a_2 x^2$

⑤ $y = \alpha x + \beta e^x$

⑥ $y = \alpha x + \beta \cos x$

data =	
1	5
2	2
4	5
5	11
8	20

data =
 (1,5)
 (2,2)
 (4,5)
 (5,11)
 (8,20)

② truncated quadratic
 $y = \alpha x + \beta x^2$
 System of linear eqns.

@ (1,5) $\alpha(1) + \beta(1)^2 = 5$
 @ (2,2) $\alpha(2) + \beta(2)^2 = 2$
 @ (4,5) $\alpha(4) + \beta(4)^2 = 5$
 @ (5,11) $\alpha(5) + \beta(5)^2 = 11$
 @ (8,20) $\alpha(8) + \beta(8)^2 = 20$

Solve
 $Ax = b$?
 inconsistent.

$A = \begin{bmatrix} 1 & 1 \\ 2 & 4 \\ 4 & 16 \\ 5 & 25 \\ 8 & 64 \end{bmatrix} \quad b = \begin{bmatrix} 5 \\ 2 \\ 5 \\ 11 \\ 20 \end{bmatrix}$
 $\uparrow \quad \uparrow$
 $\alpha\text{-coeff} \quad \beta\text{-coeff}$

to get L-S soln.
 solve normal eqns.

$ATAx = ATb$
 $\Rightarrow \hat{x} = (ATA)^{-1}ATb = \begin{bmatrix} 1.0711 \\ 0.17772 \end{bmatrix}$

So truncated quad
 best ✓

$y = 1.0711x + 0.178x^2$

Key idea:
 plug in data
 into model

Model choices 2

① $y = \alpha + \beta x$

③ $y = \alpha x + \beta x^2$

⑤ $y = a_0 + a_1x + a_2x^2 + a_3x^3$

④ $y = a_1x + a_2x^2$

⑥ $y = \alpha x + \beta e^x$

⑦ $y = \alpha x + \beta \cos x$

data =	
1	5
2	2
4	3
5	11
8	20

data =
(1,5)
(2,2)
(4,3)
(5,11)
(8,20)

model

③ Full cubic

$$y = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4$$

key idea:
plug in data
into model

@(1,5)

$$a_0 + (1)a_1 + (1)^2a_2 + (1)^3a_3 = 5$$

@(2,2)

$$a_0 + (2)a_1 + (2)^2a_2 + (2)^3a_3 = 2$$

@(4,3)

$$a_0 + (4)a_1 + (4)^2a_2 + (4)^3a_3 = 3$$

@(5,11)

$$a_0 + (5)a_1 + (5)^2a_2 + (5)^3a_3 = 11$$

@(8,20)

$$a_0 + (8)a_1 + (8)^2a_2 + (8)^3a_3 = 20$$

system of
(n+1) eq
(n+1) vars

$$Ax=b$$

$$A = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 4 & 16 & 8 \\ 4 & 16 & 64 & 64 \\ 5 & 25 & 125 & 125 \\ 8 & 64 & 512 & 512 \end{bmatrix} \quad b = \begin{bmatrix} 5 \\ 2 \\ 3 \\ 11 \\ 20 \end{bmatrix}$$

a_0 -coeff

a_1 -coeff

a_2 -coeff

unique L-S

Soln is $\hat{x} = (A^T A)^{-1} A^T b \approx$

$$\begin{bmatrix} 14.4 \\ -12.5 \\ 3.5 \\ -0.23 \end{bmatrix}$$

So best cubic is

$$y = 14.4 - 12.5x + 3.5x^2 - 0.23x^3$$

Model choices 2

① $y = \alpha + \beta x$

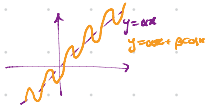
② $y = \alpha x + \beta x^2$

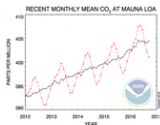
③ $y = a_0 + a_1x + a_2x^2 + a_3x^3$

④ $y = a_1x + a_2x^2$

⑤ $y = kx + pe^x$

⑥ $y = \alpha x + \beta \cos x$





Black line is yearly CO_2 levels, and the monthly is the red line. To capture seasonality, would need a curve

$$\text{daily } \text{CO}_2 = \beta_0 + \beta_1 t + \beta_2 \sin(2\pi \frac{t}{12}) + \beta_3 \cos(2\pi \frac{t}{12})$$

Above, t is time, measured in months.

Least squares problems can be computed with WolframAlpha, Mathematica, and many other software.

WolframAlpha

linear fit $\{ \{x_1, y_1\}, \{x_2, y_2\}, \dots, \{x_n, y_n\} \}$

Mathematica

LeastSquares $\{ \{ \{x_1, y_1\}, \{x_2, y_2\}, \dots, \{x_n, y_n\} \}$

Almost any spreadsheet program does this as a function as well.

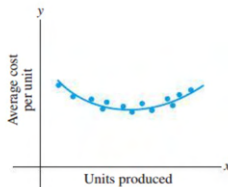


FIGURE 3

Average cost curve.

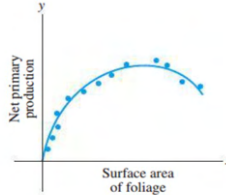


FIGURE 4

Production of nutrients.



FIGURE 5

Data points along a cubic curve.

Theorem

Theorem (Unique Solutions for Least Squares)

Let A be any $m \times n$ matrix. These statements are equivalent.

1. The equation $A\vec{x} = \vec{b}$ has a unique least-squares solution for each $\vec{b} \in \mathbb{R}^m$.
2. The columns of A are linearly independent.
3. The matrix $A^T A$ is invertible.

And, if these statements hold, the least square solution is

$$\hat{x} = (A^T A)^{-1} A^T \vec{b}.$$

Theorem (Least Squares and QR)

Let $m \times n$ matrix A have a QR decomposition. Then for each $\vec{b} \in \mathbb{R}^m$ the equation $A\vec{x} = \vec{b}$ has the unique least squares solution

$$R\vec{x} = Q^T \vec{b}.$$

(Remember, R is upper triangular, so the equation above is solved by back-substitution.)

Useful heuristic: $A^T A$ plays the role of 'length-squared' of the matrix A .
(See the sections on symmetric matrices and singular value decomposition.)

6.6 Exercises

In Exercises 1–4, find the equation $y = \beta_0 + \beta_1 x$ of the least-squares line that best fits the given data points.

- (0, 1), (1, 1), (2, 2), (3, 2)
- (1, 0), (2, 1), (4, 2), (5, 3)
- (-1, 0), (0, 1), (1, 2), (2, 4)
- (2, 3), (3, 2), (5, 1), (6, 0)

5. Let X be the design matrix used to find the least-squares line to fit data $(x_1, y_1), \dots, (x_n, y_n)$. Use a theorem in Section 6.5 to show that the normal equations have a unique solution if and only if the data include at least two data points with different x -coordinates.

6. Let X be the design matrix in Example 2 corresponding to a least-squares fit of a parabola to data $(x_1, y_1), \dots, (x_n, y_n)$. Suppose x_1, x_2 , and x_3 are distinct. Explain why there is only one parabola that fits the data best, in a least-squares sense. (See Exercise 5.)

7. A certain experiment produces the data (1, 1.8), (2, 2.7), (3, 3.4), (4, 3.8), (5, 3.9). Describe the model that produces a least-squares fit of these points by a function of the form

$$y = \beta_1 x + \beta_2 x^2$$

Such a function might arise, for example, as the revenue from the sale of x units of a product, when the amount offered for sale affects the price to be set for the product.

- Give the design matrix, the observation vector, and the unknown parameter vector.
 - [M] Find the associated least-squares curve for the data.
8. A simple curve that often makes a good model for the variable costs of a company, as a function of the sales level x , has the form $y = \beta_1 x + \beta_2 x^2 + \beta_3 x^3$. There is no constant term because fixed costs are not included.
- Give the design matrix and the parameter vector for the linear model that leads to a least-squares fit of the equation above, with data $(x_1, y_1), \dots, (x_n, y_n)$.
 - [M] Find the least-squares curve of the form above to fit the data (4, 1.58), (6, 2.08), (8, 2.5), (10, 2.8), (12, 3.1), (14, 3.4), (16, 3.8), and (18, 4.32), with values in thousands. If possible, produce a graph that shows the data points and the graph of the cubic approximation.

9. A certain experiment produces the data (1, 7.9), (2, 5.4), and (3, -9). Describe the model that produces a least-squares fit of these points by a function of the form

$$y = A \cos x + B \sin x$$

10. Suppose radioactive substances A and B have decay constants of .02 and .07, respectively. If a mixture of these two substances at time $t = 0$ contains M_A grams of A and M_B grams of B, then a model for the total amount y of the mixture present at time t is

$$y = M_A e^{-.02t} + M_B e^{-.07t} \quad (6)$$

Suppose the initial amounts M_A and M_B are unknown, but a scientist is able to measure the total amounts present at several times and records the following points (t_i, y_i) : (10, 21.34), (11, 20.68), (12, 20.05), (14, 18.87), and (15, 18.30).

- Describe a linear model that can be used to estimate M_A and M_B .
- [M] Find the least-squares curve based on (6).



Halley's Comet last appeared in 1986 and will reappear in 2061.

11. [M] According to Kepler's first law, a comet should have an elliptic, parabolic, or hyperbolic orbit (with gravitational attractions from the planets ignored). In suitable polar coordinates, the position (r, θ) of a comet satisfies an equation of the form

$$r = \beta + e(r \cdot \cos \theta)$$

where β is a constant and e is the *eccentricity* of the orbit, with $0 \leq e < 1$ for an ellipse, $e = 1$ for a parabola, and $e > 1$ for a hyperbola. Suppose observations of a newly discovered comet provide the data below. Determine the type of orbit, and predict where the comet will be when $\theta = 4.6$ (radians).³

θ	.88	1.10	1.42	1.77	2.14
r	3.00	2.30	1.65	1.25	1.01

12. [M] A healthy child's systolic blood pressure p (in millimeters of mercury) and weight w (in pounds) are approximately related by the equation

$$\beta_0 + \beta_1 \ln w = p$$

Use the following experimental data to estimate the systolic blood pressure of a healthy child weighing 100 pounds.

³ The basic idea of least-squares fitting of data is due to K. F. Gauss (and, independently, to A. Legendre), whose initial rise to fame occurred in 1801 when he used the method to determine the path of the asteroid *Ceres*. Forty days after the asteroid was discovered, it disappeared behind the sun. Gauss predicted it would appear ten months later and gave its location. The accuracy of the prediction astonished the European scientific community.

w	44	61	81	113	131
$\ln w$	3.78	4.11	4.39	4.73	4.88
p	91	98	103	110	112

13. [M] To measure the takeoff performance of an airplane, the horizontal position of the plane was measured every second, from $t = 0$ to $t = 12$. The positions (in feet) were: 0, 8.8, 29.9, 62.0, 104.7, 159.1, 222.0, 294.5, 380.4, 471.1, 571.7, 686.8, and 809.2.

a. Find the least-squares cubic curve $y = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$ for these data.

b. Use the result of part (a) to estimate the velocity of the plane when $t = 4.5$ seconds.

14. Let $\bar{x} = \frac{1}{n}(x_1 + \cdots + x_n)$ and $\bar{y} = \frac{1}{n}(y_1 + \cdots + y_n)$. Show that the least-squares line for the data $(x_1, y_1), \dots, (x_n, y_n)$ must pass through $(\bar{x}, \bar{y})$. That is, show that $\bar{x}$ and $\bar{y}$ satisfy the linear equation $\bar{y} = \beta_0 + \beta_1 \bar{x}$. [Hint: Derive this equation from the vector equation $\mathbf{y} = X\boldsymbol{\beta} + \boldsymbol{\epsilon}$. Denote the first column of X by $\mathbf{1}$. Use the fact that the residual vector $\boldsymbol{\epsilon}$ is orthogonal to the column space of X and hence is orthogonal to $\mathbf{1}$.]

Given data for a least-squares problem, $(x_1, y_1), \dots, (x_n, y_n)$, the following abbreviations are helpful:

$$\sum x = \sum_{i=1}^n x_i, \quad \sum x^2 = \sum_{i=1}^n x_i^2, \\ \sum y = \sum_{i=1}^n y_i, \quad \sum xy = \sum_{i=1}^n x_i y_i$$

The normal equations for a least-squares line $y = \beta_0 + \beta_1 x$ may be written in the form

$$n\hat{\beta}_0 + \hat{\beta}_1 \sum x = \sum y \\ \hat{\beta}_0 \sum x + \hat{\beta}_1 \sum x^2 = \sum xy \quad (7)$$

15. Derive the normal equations (7) from the matrix form given in this section.

16. Use a matrix inverse to solve the system of equations in (7) and thereby obtain formulas for $\hat{\beta}_0$ and $\hat{\beta}_1$ that appear in many statistics texts.

17. a. Rewrite the data in Example 1 with new x -coordinates in mean deviation form. Let X be the associated design matrix. Why are the columns of X orthogonal?

b. Write the normal equations for the data in part (a), and solve them to find the least-squares line, $y = \beta_0 + \beta_1 x^*$, where $x^* = x - 5.5$.

18. Suppose the x -coordinates of the data $(x_1, y_1), \dots, (x_n, y_n)$ are in mean deviation form, so that $\sum x_i = 0$. Show that if X is the design matrix for the least-squares line in this case, then $X^T X$ is a diagonal matrix.

Exercises 19 and 20 involve a design matrix X with two or more columns and a least-squares solution $\hat{\boldsymbol{\beta}}$ of $\mathbf{y} = X\boldsymbol{\beta}$. Consider the following numbers.

- (i) $\|X\hat{\boldsymbol{\beta}}\|^2$ —the sum of the squares of the “regression term.” Denote this number by $SS(R)$.
(ii) $\|\mathbf{y} - X\hat{\boldsymbol{\beta}}\|^2$ —the sum of the squares of error term. Denote this number by $SS(E)$.
(iii) $\|\mathbf{y}\|^2$ —the “total” sum of the squares of the y -values. Denote this number by $SS(T)$.

Every statistics text that discusses regression and the linear model $\mathbf{y} = X\boldsymbol{\beta} + \boldsymbol{\epsilon}$ introduces these numbers, though terminology and notation vary somewhat. To simplify matters, assume that the mean of the y -values is zero. In this case, $SS(T)$ is proportional to what is called the *variance* of the set of y -values.

19. Justify the equation $SS(T) = SS(R) + SS(E)$. [Hint: Use a theorem, and explain why the hypotheses of the theorem are satisfied.] This equation is extremely important in statistics, both in regression theory and in the analysis of variance.

20. Show that $\|X\hat{\boldsymbol{\beta}}\|^2 = \hat{\boldsymbol{\beta}}^T X^T \mathbf{y}$. [Hint: Rewrite the left side and use the fact that $\hat{\boldsymbol{\beta}}$ satisfies the normal equations.] This formula for $SS(R)$ is used in statistics. From this and from Exercise 19, obtain the standard formula for $SS(E)$:

$$SS(E) = \mathbf{y}^T \mathbf{y} - \hat{\boldsymbol{\beta}}^T X^T \mathbf{y}$$

Midterm 3 Lecture Review Activity, Math 1554

1. Indicate **true** if the statement is true, otherwise, indicate **false**.

true false

① (mini) mini-lecture on 4-Subspaces.

$$\dim S + \dim S^\perp = n$$

e.g. geo mult. > 1 . $\Rightarrow S \subseteq \mathbb{R}^n$ subspace.

- a) If S is a two-dimensional subspace of $\mathbb{R}^{50}$, then the dimension of $S^\perp$ is 48. ☒ true ☐ false
- b) An eigenspace is a subspace spanned by a single eigenvector. ☐ true ☒ false
- c) The $n \times n$ zero matrix can be diagonalized. $\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = I \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} I^{-1}$ ☒ true ☐ false
- d) A least-squares line that best fits the data points $(0, y_1), (1, y_2), (2, y_3)$ is unique for any values y_1, y_2, y_3 . ☒ true ☐ false

$$y = kx + \beta$$

plug in data into model

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 1 \\ 2 & 1 \end{bmatrix}$$

$$\begin{aligned} @ (0, y_1) & 0k + \beta = y_1 \\ @ (1, y_2) & 1k + \beta = y_2 \\ @ (2, y_3) & 2k + \beta = y_3 \end{aligned}$$

Then $\hat{x}$ L-S soln to $Ax = b$ unique

$\nRightarrow A$ has ind cols.

2. If possible, give an example of the following.

2.1) A matrix, A , that is in echelon form, and $\dim((\text{Row } A)^\perp) = 2$, $\dim((\text{Col } A)^\perp) = 1$

$$\begin{bmatrix} 1 & 2 & 3 \\ 0 & 0 & 0 \end{bmatrix}$$

$\dim(\text{Nul } A) = 2$ 2 free vars. $\checkmark$
 $\dim(\text{Nul } A^T) = 1$ A^T have 1 free

$$A^T = \begin{bmatrix} 1 & 0 \\ 2 & 0 \\ 3 & 0 \end{bmatrix} \text{ has 1 free var \& 1 pivot } \checkmark$$

2.2) A singular 2×2 matrix whose eigenspace corresponding to eigenvalue $\lambda = 2$ is the line $x_1 = 2x_2$. The other eigenspace of the matrix is the x_2 axis.

compute A via

$$A = \begin{bmatrix} 2 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 1 & 1 \end{bmatrix}^{-1} = \begin{bmatrix} 2 & 0 \\ 1 & 0 \end{bmatrix}$$

$P \quad D \quad P^{-1}$
 $\uparrow \quad \uparrow$
come up w/ P s.t. D first.

λ -eigenspace

$$\text{Nul}(A - \lambda I)$$

$$\lambda = 0$$

$$\text{Nul}(A - 0I)$$

$$\equiv \text{Nul } A$$

2.3) A subspace S , of $\mathbb{R}^4$, that satisfies $\dim(S) = \dim(S^\perp) = 3$.

NP

$$\begin{bmatrix} 2 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \end{bmatrix}$$

$\dim S + \dim S^\perp$ must be 4.

two other also don't work

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$A = \begin{bmatrix} -3 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$\text{Nul } A$ plane not spans $\{ \frac{2}{3}, 1 \}$

2.4) A 2×3 matrix, A , that is in RREF. $(\text{Row } A)^\perp$ is spanned by

$$\begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix}$$

$$(\text{Row } A)^\perp = \text{Nul } A = \text{span} \left\{ \begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix} \right\}$$

$$\begin{aligned} a &= -2 \\ b &= -3 \end{aligned}$$

$$\begin{aligned} 2 + a &= 0 \\ 3 + b &= 0 \end{aligned}$$

$$A = \begin{bmatrix} 1 & 0 & -2 \\ 0 & 1 & -3 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & a \\ 0 & 1 & b \end{bmatrix} \begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

(mini) mini lecture on Four Subspaces.

① $\text{Col } A$

③ $(\text{Col } A)^\perp = \text{Nul}(A^T)$

② $\text{Nul } A$

④ $(\text{Nul } A)^\perp = \text{Row } A$

W subspace of $\mathbb{R}^n$ then

$$W^\perp = \{ \vec{x} \in \mathbb{R}^n \mid \vec{x} \cdot \vec{w} = 0 \text{ for every } \vec{w} \in W \}$$

$$\vec{x} \in \text{Nul } A \iff A\vec{x} = \vec{0}$$

$$\vec{y} \in (\text{Nul } A)^\perp = \text{Row } A \iff \text{whenever } \vec{x} \text{ satisfies } A\vec{x} = \vec{0} \text{ then}$$

$$A\vec{x} = \vec{0}$$

$$\vec{y} \cdot \vec{x} = 0$$

$$\begin{bmatrix} 1 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\uparrow \vec{x} = \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} \in \text{Nul} \begin{pmatrix} 1 & 1 & 0 \\ 0 & 2 & 1 \end{pmatrix}$$

$$\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} = 0$$

$$\begin{bmatrix} 0 \\ 2 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} = 0$$

If you believe

$$(\text{Row } A)^\perp = \text{Nul } A$$

Then consider what happens when you replace A w/ A^T

$$(\text{Col } A)^\perp = (\text{Row } A^T)^\perp = \text{Nul } A^T$$

3. Circle **possible** if the set of conditions create a situation that is possible, otherwise, circle **impossible**. For the situations that are possible give an example.

3.1) A is $n \times n$, $A\vec{x} = A\vec{y}$ for a particular $\vec{x} \neq \vec{y}$, $\vec{x}$ and $\vec{y}$ are in $\mathbb{R}^n$, and $\dim((\text{Row } A)^\perp) \neq 0$.

possible ~~impossible~~ $\dim(\text{Nul } A) \neq 0$
 A is singular

3.2) A is $n \times n$, $\lambda \in \mathbb{R}$ is an eigenvalue of A , and $\dim((\text{Col}(A - \lambda I))^\perp) \neq 0$.

possible ~~impossible~~

$$\dim(\text{Nul}(A - \lambda I)) \geq 1.$$

$\text{Nul}(A - \lambda I) \subseteq \mathbb{R}^n$
 subspace.

$$\text{rank}(A - \lambda I) < n$$

$$\dim \text{Col}(A - \lambda I) < n$$

$$\text{So } (\text{Col}(A - \lambda I))^\perp \geq 1$$

3.3) $\text{proj}_{\vec{u}} \vec{u} = \text{proj}_{\vec{u}} \vec{v}$, $\vec{v} \neq \vec{u}$, and $\vec{u} \neq \vec{0}$, $\vec{v} \neq \vec{0}$.

possible

impossible

try.

$$\vec{u} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \vec{v} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \text{check if it works or not.}$$

4. Consider the matrix A .

$$A = \begin{pmatrix} 1 & -3 & 0 & 2 \\ 0 & 0 & 1 & -3 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$x_1 = 3 - 2s$$

$$x_2 = r \text{ free}$$

$$x_3 = 3s$$

$$x_4 = s \text{ free}$$

$$\vec{x} = \begin{bmatrix} 3r - 2s \\ r \\ 3s \\ s \end{bmatrix} = r \begin{bmatrix} 3 \\ 1 \\ 0 \\ 0 \end{bmatrix} + s \begin{bmatrix} -2 \\ 0 \\ 3 \\ 1 \end{bmatrix}$$

Construct a basis for the following subspaces and state the dimension of each.

4.1) $(\text{Row } A)^\perp$

4.2) $\text{Col } A$

4.3) $(\text{Col } A)^\perp$

4.4) $\text{Row } A$

4.2 basis for $\text{Col } A$ is $\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$

4.4 basis for $\text{Row } A$ is $\left\{ \begin{bmatrix} 1 \\ -3 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ -3 \end{bmatrix} \right\}$

4.1 $(\text{Row } A)^\perp = \text{Nul } A$ basis is $\left\{ \begin{bmatrix} 3 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -2 \\ 0 \\ 3 \\ 1 \end{bmatrix} \right\}$

4.3 $(\text{Col } A)^\perp$ basis is $\left\{ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$

Suppose $\lambda=0$ is an eigenvalue of A .

$$\lambda=0 \Rightarrow \boxed{A\vec{x} = 0\vec{x}} \text{ for some } \underline{\vec{x} \neq \vec{0}}$$
$$\Rightarrow \boxed{A\vec{x} = \vec{0}} \quad \vec{x} \in \text{Null } A.$$

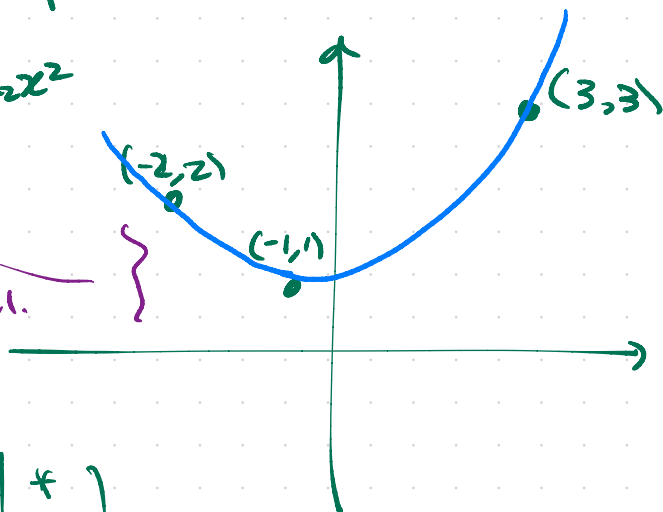
$$A\vec{x} = \lambda\vec{x}$$

So A has a
free var since
it has nonzero
vectors in
its null space.

polynomial interpolation

$$y = a_0 + a_1x + a_2x^2$$

plug
in data
into model.



$$\left(\begin{array}{ccc|c} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{array} \right)$$

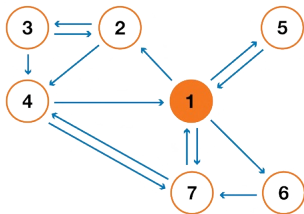
coeff
matrix.

y-values,

most often
consistent w/ curve
soln.

Chapter 10 : Finite-State Markov Chains

10.2 : The Steady-State Vector and Page Rank



Trajectory : 1

Topics and Objectives

Topics

1. Review of Markov chains
2. Theorem describing the steady state of a Markov chain
3. Applying Markov chains to model website usage.
4. Calculating the PageRank of a web.

Learning Objectives

1. Determine whether a stochastic matrix is regular.
2. Apply matrix powers and theorems to characterize the long-term behaviour of a Markov chain.
3. Construct a transition matrix, a Markov Chain, and a Google Matrix for a given web, and compute the PageRank of the web.

Chapter 10 : Finite-State Markov Chains
10.2 : The Steady-State Vector and Page Rank



Topics and Objectives

Topics

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Course Schedule

Cancellations due to inclement weather will likely result in cancelling review lectures and possibly moving through course material at a faster pace.

Week Dates	Mon Lecture	Tue Studio	Wed Lecture	Thu Studio	Fri Lecture
1 8/21 - 8/25	1.1	WS1.1	1.2	WS1.2	1.3
2 8/28 - 9/1	1.4	WS1.3, 1.4	1.5	WS1.5	1.7
3 9/4 - 9/8	Break	WS1.7	1.8	WS1.8	1.9
4 9/11 - 9/15	2.1	WS1.9, 2.1	Exam 1, Review	Cancelled	2.2
5 9/18 - 9/22	2.3, 2.4	WS2.2, 2.3	2.5	WS2.4, 2.5	2.8
6 9/25 - 9/29	2.9	WS2.8, 2.9	3.1, 3.2	WS3.1, 3.2	3.3
7 10/2 - 10/6	4.9	WS3.4, 4.9	5.1, 5.2	WS5.1, 5.2	5.2
8 10/9 - 10/13	Break	Break	Exam 2, Review	Cancelled	5.3
9 10/16 - 10/20	5.3	WS5.3	5.5	WS5.5	6.1
10 10/23 - 10/27	6.1, 6.2	WS6.1	6.2	WS6.2	6.3
11 10/30 - 11/3	6.4	WS6.3, 6.4	6.4, 6.5	WS6.4, 6.5	6.5
12 11/6 - 11/10	6.6	WS6.5, 6.6	Exam 3, Review	Cancelled	PageRank
13 11/13 - 11/17	7.1	WS7.1, 7.2	7.2	WS7.1, 7.2	7.3
14 11/20 - 11/24	7.3, 7.4	WS7.2, 7.3	Break	Break	Break
15 11/27 - 12/1	7.4	WS7.3, 7.4	7.4	WS7.4	7.4
16 12/4 - 12/8	Last lecture	Last Studio	Reading Period		
17 12/11 - 12/15	Final Exams: MATH 1554 Common Final Exam Tuesday, December 12th at 8pm				

§10.2 PageRank.
Google Matrix.

Where is Chapter 10?

- The material for this part of the course is covered in Section 10.2
- Chapter 10 is not included in the print version of the book, but it is in the on-line version.
- If you read 10.2, and I recommend that you do, you will find that it requires an understanding of 10.1.
- You are not required to understand the material in 10.1.

- Other sources that you may find helpful are listed below.
1. PageRank Algorithms (Math Explorer's Club, Cornell Univ.)
<http://www.math.cornell.edu/~mec/Winter2009/Raischman/Lectures/Lecture3.html>
 2. Austin, D. How Google Finds Your Needle in the Web's Haystack
Available at: <http://www.sas.org/sasj/insights/features/columns/feature-page-rank>
 3. Bryan, K., Leslie, T. The \$25,000,000,000 Eigenvector: The Linear Algebra behind Google's PageRank, 4th ed. Available at: <http://users.gps.uvic.ca/~bryan/teaching/4830/GooglePageRank.pdf>

Steady State Vectors

Recall the car rental problem from our Section 4.1 lecture.

Problem

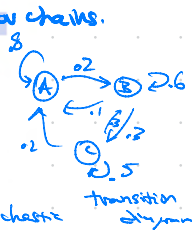
A car rental company has 3 rental locations, A, B, and C.

	rented from		
	A	B	C
returned to	A	B	C
	8	1	2
	B	2	6
	C	0	3
	5		

There are 10 cars at each location today, what happens to the distribution of cars after a long time?

Stochastic matrix, columns are prob vector $X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$ ($x_1 \geq 0, x_2 \geq 0, x_3 \geq 0, x_1 + x_2 + x_3 = 1$).

$$P = \begin{pmatrix} \frac{8}{15} & \frac{1}{9} & \frac{2}{9} \\ \frac{2}{9} & \frac{6}{9} & \frac{3}{9} \\ 0 & \frac{3}{9} & \frac{5}{9} \end{pmatrix}$$



Q₁: what is long term trend?
Q₂: is there a prob vector steady state
P_{ss} = $\vec{q}$ (q eigenvector of $A=1$)

Q₃: THM if P regular, then answer to Q₁ & Q₂ are both yes and the same thing $\vec{q}$.

Long Term Behaviour

- Can use the transition matrix, P , to find the distribution of cars after 1 week:
- $$\vec{x}_1 = P\vec{x}_0$$
- The distribution of cars after 2 weeks is:
- $$\vec{x}_2 = P^2\vec{x}_0$$
- The distribution of cars after n weeks is:
- $$\vec{x}_n = P^n\vec{x}_0$$

what is the limit of $P^n\vec{x}_0$ if $n \rightarrow \infty$?

Long Term Behaviour

- To investigate the long-term behaviour of a system that has a regular transition matrix P^n we could:
1. compute $P^n\vec{x}_0$ for large n .
 2. compute the steady-state vector, $\vec{q}$, by solving $\vec{q} = P\vec{q}$.
- To solve PageRank problems, we will rely on the first approach.

$Nu(P-I)$

Defn: P is regular if P^n has only pos entries for some $n \geq 1$.

Theorem 1

If P is a regular $n \times m$ transition matrix with $m \geq 2$, then the following statements are true.

1. There is a stochastic matrix Π such that

$$\lim_{n \rightarrow \infty} P^n = \Pi$$

2. Each column of Π is the same probability vector $\vec{q}$.

3. For any initial probability vector $\vec{x}_0$,

$$\lim_{n \rightarrow \infty} P^n \vec{x}_0 = \vec{q}$$

4. P has a unique eigenvector, $\vec{q}$, which has eigenvalue $\lambda = 1$.

5. The eigenvalues of P satisfy $|\lambda| \leq 1$.

We will apply this theorem when solving PageRank problems.

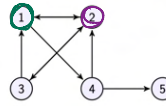
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```
clc
format bank
%% rental car - long term analysis
A=[.8 .1 .2 ; .2 .6 .3 ; 0 .3 .5]
k=10
A^k
```

```
%% google PageRank
P0=[0 1/2 1/2 0 1/5 ;
    1/2 0 1/2 1/2 1/5 ;
    0 1/2 0 0 1/5 ;
    1/2 0 0 0 1/5 ;
    0 0 0 1/2 1/5];
K0=(1/5)*[1 1 1 1 1 ;
    1 1 1 1 1 ;
    1 1 1 1 1 ;
    1 1 1 1 1 ;
    1 1 1 1 1];
G0=.85*P0+.15*K0;
P1=[0 0 1 0 1/5 ;
    1/3 0 0 1/2 1/5 ;
    1/3 0 0 1/2 1/5 ;
    1/3 1/2 0 0 1/5 ;
    0 1/2 0 0 1/5];
G1=.85*P1+.15*K0;
P2=[0 1/2 0 1/7 0 1/7 ;
    0 0 1/3 1/7 1/2 0 1/7 ;
    1 0 0 1/7 0 1/3 1/7 ;
    0 0 1/3 1/7 0 0 1/7 ;
    0 1/2 0 1/7 0 0 1/7 ;
    0 0 1/3 1/7 1/2 1/3 1/7 ;
    0 0 0 1/7 0 1/3 1/7];
K2=1/7*[1 1 1 1 1 1 1 ;
    1 1 1 1 1 1 1 ;
    1 1 1 1 1 1 1 ;
    1 1 1 1 1 1 1 ;
    1 1 1 1 1 1 1 ;
    1 1 1 1 1 1 1 ;
    1 1 1 1 1 1 1];
G2=.85*P2+.15*K2;
k=20;
test=[1 1 1 1 1 1 1] * G2;
format short
for i=1:k
    i;
    G1^i;
end
```

Example 1

Suppose we have 4 web pages that link to each other according to this diagram.



Page 1 has links to pages 2, 4

Page 2 has links to pages 3, 1

Step 1: define P from the link diagram

$$P = \begin{bmatrix} 0 & .5 & .5 & 0 & 0 \\ .5 & 0 & .5 & .5 & 0 \\ 0 & .5 & 0 & 0 & 0 \\ .5 & 0 & 0 & .5 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

If a user on a page in this web is **equally likely** to go to any of the pages that their page links to, construct a Markov chain that represents how users navigate this web.

Step 2: first adjustment

$$P^* = \begin{bmatrix} 0 & .5 & .5 & 0 & .2 \\ .5 & 0 & .5 & .5 & .2 \\ 0 & .5 & 0 & 0 & .2 \\ .5 & 0 & 0 & .5 & .2 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Step 3: second adjustment

$$G = (.85) \begin{bmatrix} 0 & .5 & .5 & 0 & .2 \\ .5 & 0 & .5 & .5 & .2 \\ 0 & .5 & 0 & 0 & .2 \\ .5 & 0 & 0 & .5 & .2 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} + (.15) \begin{bmatrix} .2 & .2 & .2 & .2 & 1 \\ .2 & .2 & .2 & .2 & 1 \\ .2 & .2 & .2 & .2 & 1 \\ .2 & .2 & .2 & .2 & 1 \\ .2 & .2 & .2 & .2 & 1 \end{bmatrix}$$

Transition Matrix, Importance, and PageRank

- The square matrix we constructed in the previous example is a **transition matrix**. It describes how users transition between pages in the web.
- The steady-state vector $\vec{q}$ of the Markov-chain, can characterize the long-term behavior of users in a given web.
- If $\vec{q}$ is unique, the **importance** of a page in a web is given by its corresponding entry in $\vec{q}$.
- The **PageRank** is the ranking assigned to each page based on its importance. The highest ranked page has PageRank 1, the second PageRank 2, and so on.

Is the transition matrix in Example 1 a regular matrix?

$$q = \begin{bmatrix} 0.25171 \\ 0.29855 \\ 0.17655 \\ 0.15677 \\ 0.11641 \end{bmatrix}$$

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$$G^{10} \approx [\vec{q} \vec{q} \vec{q} \vec{q} \vec{q}]$$

Adjustment 1

Adjustment 1

If a user reaches a page that doesn't link to other pages, then the user will choose any page in the web, with equal probability, and move to that page.

Let's denote this modified transition matrix as P^* . Our transition matrix in Example 1 becomes:

Adjustment 2

Adjustment 2

A user at any page will navigate any page among those that their page links to with equal probability p , and to any page in the web with equal probability $1 - p$. The transition matrix becomes

$$G = pP^* + (1 - p)K$$

All the elements of the $n \times n$ matrix K are equal to $1/n$.

p is referred to as the **damping factor**, Google is said to use $p = 0.85$.

With adjustments 1 and 2, our the Google matrix is:

Computing Page Rank

- Because G is stochastic, for any initial probability vector $\vec{x}_0$,

$$\lim_{n \rightarrow \infty} G^n \vec{x}_0 = \vec{q}$$

- In practice we can compute the page rank for each page in the web by evaluating

$$G^n \vec{x}_0$$

for large n . The elements of the resulting vector give the page ranks of each page in the web.

On a MATH 1594 exam,

- problems that require a calculator will not be on your exam

you may construct your G matrix using fractions instead of decimal expansions

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Section 10.2 Slide 269

transition matrix with $m \geq 2$, then the following

matrix Π such that

$$\lim_{n \rightarrow \infty} P^n = \Pi$$

same probability vector $\vec{q}$.

$$\lim_{n \rightarrow \infty} P^n \vec{x}_0 = \vec{q}$$

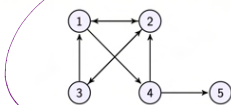
vector, $\vec{q}$, which has eigenvalue $\lambda = 1$.

satisfy $|\lambda| \leq 1$.

When solving PageRank problems.

Example 1

Suppose we have 4 web pages that link to each other according to this diagram.



Page 1 has links to pages _____.

Page 2 has links to pages _____.

If a user on a page in this web is **equally likely** to go to any of the pages that their page links to, construct a Markov chain that represents how users navigate this web.

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$$G \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} = \vec{s}$$

Says the prob vector for where you end up after 2 choices starting w/ $\begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}$ = 100% on page 2.

43% chance to be on page 2 starting on either 2 choices

Command Window

New to MATLAB? See resources for [Getting Started](#).

```

P =
    0    0.5    0.5    0    0
    0.5    0    0.5    0    0
    0    0.5    0    0    0
    0    0    0    0    0
    0    0    0    0.5    0.2

k =
    0.2    0.2    0.2    0.2    0.2
    0.2    0.2    0.2    0.2    0.2
    0.2    0.2    0.2    0.2    0.2
    0.2    0.2    0.2    0.2    0.2
    0.2    0.2    0.2    0.2    0.2

s = 0.5P + 0.15K regular stochastic
    0.03    0.455    0.455    0.03    0.2
    0.455    0.03    0.455    0.455    0.2
    0.03    0.455    0.03    0.03    0.2
    0.455    0.03    0.03    0.03    0.2
    0.03    0.03    0.03    0.455    0.2

G^1 =
    0.03    0.455    0.455    0.03    0.2
    0.455    0.03    0.455    0.455    0.2
    0.03    0.455    0.03    0.03    0.2
    0.455    0.03    0.03    0.03    0.2
    0.03    0.03    0.03    0.455    0.2

G^2 =
    0.24122    0.43438    0.24122    0.31347    0.234
    0.23397    0.23397    0.23397    0.14864    0.318
    0.22847    0.04785    0.22847    0.30073    0.149
    0.04785    0.22847    0.22847    0.1201    0.149
    0.22847    0.04785    0.04785    0.1201    0.149

G^3 =
    0.27398    0.28318    0.28318    0.24011    0.25423
    0.2888    0.23509    0.23509    0.34249    0.28143
    0.17678    0.22284    0.14607    0.1123    0.1909
    0.17136    0.14066    0.14066    0.18364    0.15478
    0.089177    0.13524    0.13524    0.10146    0.11865

G^4 =
    0.24303    0.25739    0.25739    0.24903    0.25091
    0.30952    0.31083    0.2782    0.27507    0.30514
    0.1479    0.14248    0.19331    0.20131    0.14978
    0.14156    0.15634    0.15634    0.14929    0.15822
    0.11799    0.11277    0.11277    0.1253    0.11595

G^5 =
    0.25296    0.25041    0.25041    0.25376    0.25155
    0.29337    0.29414    0.30801    0.30615    0.29575
    0.1816    0.18127    0.14741    0.14602    0.17939
    0.15335    0.15856    0.15856    0.15714    0.15635
    0.11872    0.11562    0.11562    0.11475    0.11696

G^6 =
    0.25205    0.25171    0.25171    0.25111    0.25182
    0.30005    0.30051    0.29461    0.29583    0.29948
    0.17484    0.17487    0.16056    0.17862    0.17588
    0.15769    0.15608    0.15608    0.15736    0.15679
    0.11535    0.11704    0.11704    0.11629    0.11633

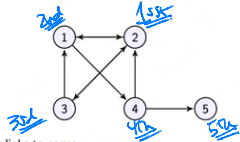
G^7 =
    0.25145    0.25185    0.25185    0.25175    0.25169
    0.29507    0.29744    0.29694    0.2997    0.29806
    0.17713    0.17761    0.17511    0.17541    0.17706
    0.15673    0.15687    0.15687    0.15649    0.1566
    0.11663    0.11623    0.11623    0.11665    0.11641

G^8 =
    0.25176    0.25166    0.25166    0.25176    0.25171
    0.29658    0.29695    0.29785    0.29738    0.29624
    0.1765    0.17617    0.17724    0.1772    0.17646
    0.15669    0.15679    0.15679    0.15682    0.15675
    0.11644    0.11643    0.11643    0.11634    0.11643

G^9 =
    0.25171    0.25172    0.25172    0.25169    0.25171
    0.29841    0.29826    0.29871    0.29873    0.29839
    0.17669    0.17685    0.17639    0.17638    0.17672
    0.1566    0.15675    0.15675    0.15677    0.15677
    0.11639    0.11643    0.11643    0.11643    0.11642
  
```

Example 1

Suppose we have 4 web pages that link to each other according to this diagram.



Page 1 has links to pages _____.

Page 2 has links to pages _____.

If a user on a page in this web is **equally likely** to go to any of the pages that their page links to, construct a Markov chain that represents how users navigate this web.

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$$q = \begin{pmatrix} 0.25171 \\ 0.29655 \\ 0.17655 \\ 0.15677 \\ 0.11641 \end{pmatrix}$$

Prob end up at pg 2 starting w/ pg 1 after 10 steps

Command Window

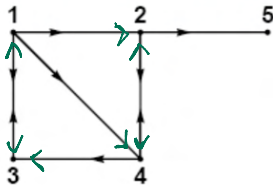
New to MATLAB? See resources for [Getting Started](#).

```

G^10 =
    0.2517    0.2517    0.2517    0.2517    0.2517
    0.2966    0.2966    0.2966    0.2966    0.2966
    0.1766    0.1766    0.1766    0.1766    0.1766
    0.1567    0.1567    0.1567    0.1567    0.1567
    0.1164    0.1164    0.1164    0.1164    0.1164
  
```

Chance you end up at page 2 if started at page 2 after 10 choices.

links diagram matrix eq/ first adjustment



$$P^* = \begin{bmatrix} 0 & 0 & 1 & 0 & .2 \\ 1/3 & 0 & 0 & 1/2 & .2 \\ 1/3 & 0 & 0 & 1/2 & .2 \\ 1/3 & 1/2 & 0 & 0 & .2 \\ 0 & 1/2 & 0 & 0 & .2 \end{bmatrix}$$

$$K = \begin{bmatrix} .2 & .2 & .2 & .2 & .2 \\ .2 & .2 & .2 & .2 & .2 \\ .2 & .2 & .2 & .2 & .2 \\ .2 & .2 & .2 & .2 & .2 \\ .2 & .2 & .2 & .2 & .2 \end{bmatrix}$$

$$G = .85P^* + .15K$$

Command Window

New to MATLAB? See resources for [Getting Started](#)

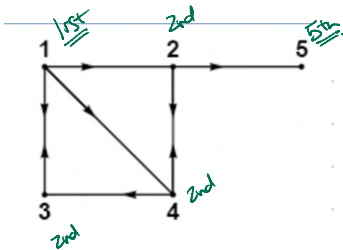
P1 =					
0	0	1	0	0.2	
0.33333	0	0	0.5	0.2	
0.33333	0	0	0.5	0.2	
0.33333	0.5	0	0	0.2	
0	0.5	0	0	0.2	
K0 =					
0.2	0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2	0.2
G = .85P* + .15K					
0.03	0.03	0.88	0.03	0.2	
0.31333	0.03	0.03	0.455	0.2	
0.31333	0.03	0.03	0.455	0.2	
0.31333	0.455	0.03	0.03	0.2	
0.03	0.455	0.03	0.03	0.2	
G*2 =					
0.30143	0.13285	0.0606	0.42185	0.234	
0.17477	0.30922	0.29718	0.05435	0.20567	
0.17477	0.30922	0.29718	0.05435	0.20567	
0.17477	0.1206	0.29718	0.23697	0.20567	
0.14827	0.1201	0.04785	0.22847	0.149	
G*3 =					
0.20886	0.31326	0.29074	0.11674	0.23015	
0.21914	0.14271	0.18161	0.28908	0.20904	
0.21914	0.14271	0.18161	0.28908	0.20904	
0.21914	0.21948	0.18161	0.21231	0.20904	
0.13373	0.18184	0.16444	0.092789	0.14274	
G*4 =					
0.239	0.18222	0.21232	0.29149	0.23195	
0.20504	0.24295	0.21751	0.14908	0.20832	

Command Window

New to MATLAB? See resources for [Getting Started](#)

G*5 =					
0.239	0.18222	0.21232	0.29149	0.23195	
0.20504	0.24295	0.21751	0.14908	0.20832	
0.20504	0.24295	0.21751	0.14908	0.20832	
0.20504	0.21032	0.21751	0.20171	0.20832	
0.14857	0.12157	0.13514	0.16863	0.14311	
G*6 =					
0.23008	0.23717	0.23786	0.20239	0.2314	
0.20966	0.19148	0.20557	0.22498	0.20858	
0.20966	0.19148	0.20557	0.22498	0.20858	
0.20966	0.20555	0.20557	0.21312	0.20858	
0.14314	0.15392	0.14542	0.13053	0.14256	
G*7 =					
0.23034	0.21391	0.22946	0.24513	0.23158	
0.20814	0.21439	0.20948	0.20011	0.2085	
0.20814	0.21439	0.20948	0.20011	0.2085	
0.20814	0.2105	0.20948	0.206	0.2085	
0.14323	0.13763	0.14209	0.14866	0.14293	
G*8 =					
0.23127	0.23733	0.23222	0.22536	0.23152	
0.20864	0.20494	0.2082	0.21227	0.20852	
0.20864	0.20494	0.2082	0.21227	0.20852	
0.20864	0.20744	0.2082	0.20977	0.20852	
0.14281	0.14536	0.14319	0.14032	0.14291	
G*9 =					
0.23142	0.22891	0.23131	0.23429	0.23154	
0.20848	0.21012	0.20862	0.20686	0.20851	
0.20848	0.21012	0.20862	0.20686	0.20851	
0.20848	0.20905	0.20862	0.20752	0.20851	
0.14295	0.14181	0.14283	0.14407	0.14292	
G*10 =					
0.23151	0.23271	0.23141	0.23032	0.23153	
0.20853	0.20781	0.20848	0.20924	0.20852	
0.20853	0.20781	0.20848	0.20924	0.20852	
0.20853	0.20826	0.20848	0.20879	0.20852	
0.1429	0.14341	0.14294	0.14241	0.14291	
G*11 =					
0.23154	0.23102	0.23151	0.23206	0.23154	
0.20851	0.20882	0.20853	0.2082	0.20852	
0.20851	0.20882	0.20853	0.2082	0.20852	
0.20851	0.20863	0.20853	0.20839	0.20852	
0.14292	0.1427	0.14291	0.14314	0.14292	

$$\hat{G} = \begin{bmatrix} 0.23154 \\ 0.20851 \\ 0.20851 \\ 0.20851 \\ 0.14292 \end{bmatrix}$$



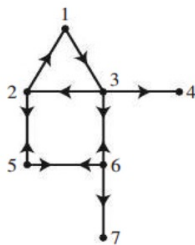
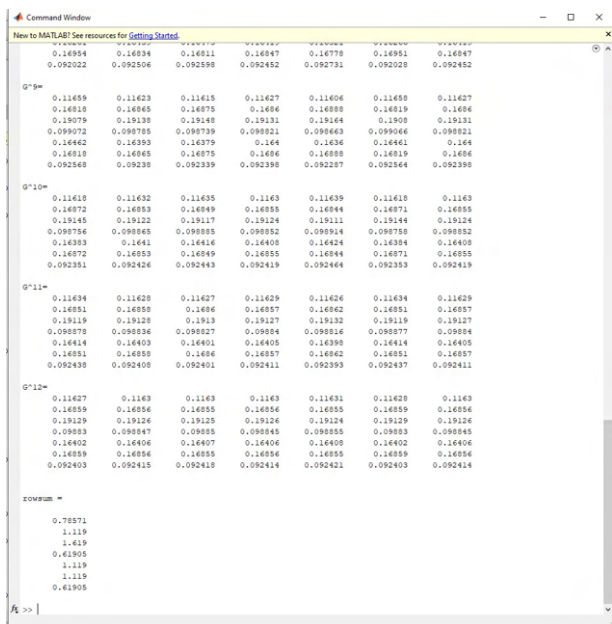
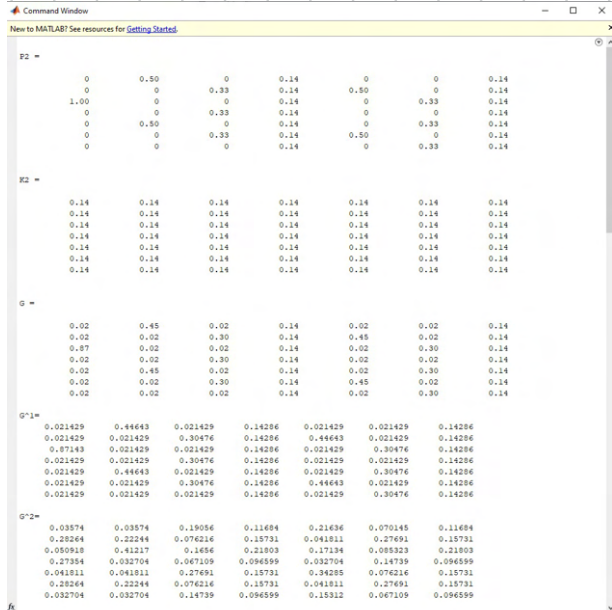


FIGURE 1
A seven-page Web.



Example 2 (if time permits)

Construct the Google Matrix for the web below (your instructor would provide the web).

There is (of course) Much More to PageRank



The PageRank Algorithm currently used by Google is under constant development, and tailored to individual users.

- When PageRank was devised, in 1996, Yahoo! used humans to provide a "index for the Internet," which was 10 million pages.
- The PageRank algorithm was produced as a competing method. The patent was awarded to Stanford University, and exclusively licensed to the newly formed Google corporation.
- Brin and Page combined the PageRank algorithm with a webcrawler to provide regular updates to the transition matrix for the web.
- The explosive growth of the web soon overwhelmed human based approaches to searching the internet.

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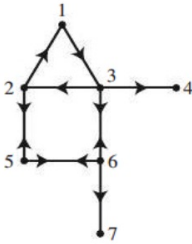
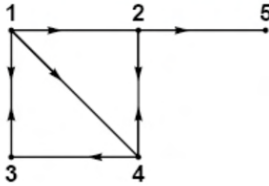


FIGURE 1
A seven-page Web.

DEFINITION

A stochastic matrix P is **regular** if some power P^k contains only strictly positive entries.

THEOREM 1

If P is a regular $m \times m$ transition matrix with $m \geq 2$, then the following statements are all true.

- There is a stochastic matrix Π such that $\lim_{n \rightarrow \infty} P^n = \Pi$.
- Each column of Π is the same probability vector $\mathbf{q}$.
- For any initial probability vector $\mathbf{x}_0$, $\lim_{n \rightarrow \infty} P^n \mathbf{x}_0 = \mathbf{q}$.
- The vector $\mathbf{q}$ is the unique probability vector which is an eigenvector of P associated with the eigenvalue 1.
- All eigenvalues λ of P other than 1 have $|\lambda| < 1$.

10.2 Exercises

In Exercises 1 and 2, consider a Markov chain on $\{1, 2\}$ with the given transition matrix P . In each exercise, use two methods to find the probability that, in the long run, the chain is in state 1. First, raise P to a high power. Then directly compute the steady-state vector.

$$1. P = \begin{bmatrix} .2 & .4 \\ .8 & .6 \end{bmatrix} \quad 2. P = \begin{bmatrix} 1/4 & 2/3 \\ 3/4 & 1/3 \end{bmatrix}$$

In Exercises 3 and 4, consider a Markov chain on $\{1, 2, 3\}$ with the given transition matrix P . In each exercise, use two methods to find the probability that, in the long run, the chain is in state 1.

First, raise P to a high power. Then directly compute the steady-state vector.

$$3. P = \begin{bmatrix} 1/3 & 1/4 & 0 \\ 1/3 & 1/2 & 1 \\ 1/3 & 1/4 & 0 \end{bmatrix} \quad 4. P = \begin{bmatrix} .1 & .2 & .3 \\ .2 & .3 & .4 \\ .7 & .5 & .3 \end{bmatrix}$$

In Exercises 5 and 6, find the matrix to which P^n converges as n increases.

$$5. P = \begin{bmatrix} 1/4 & 2/3 \\ 3/4 & 1/3 \end{bmatrix} \quad 6. P = \begin{bmatrix} 1/4 & 3/5 & 0 \\ 1/4 & 0 & 1/3 \\ 1/2 & 2/5 & 2/3 \end{bmatrix}$$

In Exercises 7 and 8, determine whether the given matrix is regular. Explain your answer.

$$7. P = \begin{bmatrix} 1/3 & 0 & 1/2 \\ 1/3 & 1/2 & 1/2 \\ 1/3 & 1/2 & 0 \end{bmatrix}$$

$$8. P = \begin{bmatrix} 1/2 & 0 & 1/3 & 0 \\ 0 & 2/5 & 0 & 3/7 \\ 1/2 & 0 & 2/3 & 0 \\ 0 & 3/5 & 0 & 4/7 \end{bmatrix}$$

9. Consider a pair of Ehrenfest urns with a total of 4 molecules divided between them.

- Find the transition matrix for the Markov chain that models the number of molecules in urn A, and show that this matrix is not regular.
- Assuming that the steady-state vector may be interpreted as occupation times for this Markov chain, in what state will this chain spend the most steps?

10. Consider a pair of Ehrenfest urns with a total of 5 molecules divided between them.

- Find the transition matrix for the Markov chain that models the number of molecules in urn A, and show that this matrix is not regular.
- Assuming that the steady-state vector may be interpreted as occupation times for this Markov chain, in what state will this chain spend the most steps?

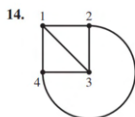
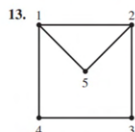
11. Consider an unbiased random walk with reflecting boundaries on $\{1, 2, 3, 4\}$.

- Find the transition matrix for the Markov chain and show that this matrix is not regular.
- Assuming that the steady-state vector may be interpreted as occupation times for this Markov chain, in what state will this chain spend the most steps?

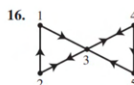
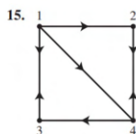
12. Consider a biased random walk with reflecting boundaries on $\{1, 2, 3, 4\}$ with probability $p = .2$ of moving to the left.

- Find the transition matrix for the Markov chain and show that this matrix is not regular.
- Assuming that the steady-state vector may be interpreted as occupation times for this Markov chain, in what state will this chain spend the most steps?

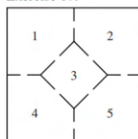
In Exercises 13 and 14, consider a simple random walk on the given graph. In the long run, what fraction of the time will the walk be at each of the various states?



In Exercises 15 and 16, consider a simple random walk on the given directed graph. In the long run, what fraction of the time will the walk be at each of the various states?

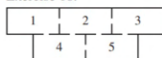


17. Consider the mouse in the following maze from Section 10.1, Exercise 17.



The mouse must move into a different room at each time step and is equally likely to leave the room through any of the available doorways. If you go away from the maze for a while, what is the probability that the mouse will be in room 3 when you return?

18. Consider the mouse in the following maze from Section 10.1, Exercise 18.



What fraction of the time does it spend in room 3?

19. Consider the mouse in the following maze, which includes "one-way" doors, from Section 10.1, Exercise 19.



Show that

$$\mathbf{q} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

is a steady-state vector for the associated Markov chain, and interpret this result in terms of the mouse's travels through the maze.

