Elementary Graph Theory & Matrix Algebra

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Introduction

- In social network analysis, we draw on three major areas of mathematics regularly:
  - Binary Relations / Set Theory
    - Branch of math that deals with mappings between sets, such as objects to real numbers (measurement) or people to people (social relations)
  - Graph Theory
    - Branch of discrete math that deals with collections of ties among nodes and gives us concepts like paths
  - Matrix Algebra
    - Tables of numbers
    - Operations on matrices enable us to draw conclusions we couldn’t just intuit

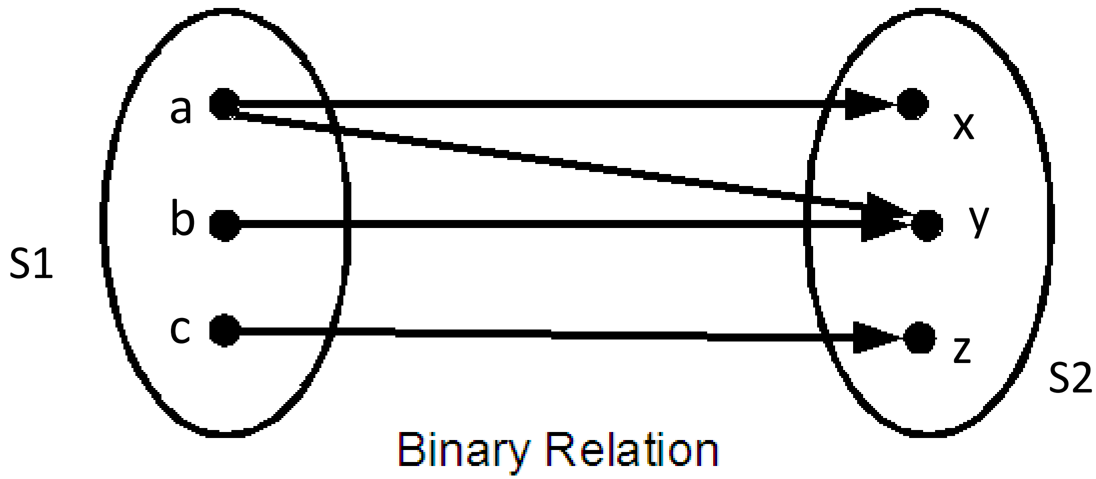
BINARY RELATIONS / SET THEORY

Cartesian Product

- Given two sets, S1 and S2, the Cartesian product S1×S2 is the set of all possible ordered pairs (u,v) in which $u \in S1$ and $v \in S2$
- Example:
  - S1 = {a,b,c}
  - S2 = {x,y}
  - S1×S2 = { (a,x),(a,y),(b,x),(b,y),(c,x),(c,y) }

Binary Relations

- Given sets S1 and S2, a binary relation R is a subset of their Cartesian product



Note: S1 and S2 could be the same set

- R = { (a,x), (a,y), (b,y), (c,z) }

Relational Terminology

- To indicate that “u is R-related to v” or “u is mapped to v by the relation R”, we write
  - (u,v) ∈ R, or
  - uRv
- Example: If R is “likes”, then
  - uRv says u likes v
  - (jim,jane) ∈ R says jim likes jane

Properties of Relations

- A relation is *reflexive* if for all u, (u,u)$\in$R
  - E.g., suppose R is "is in the same room as"
  - u is always in the same room as u, so the relation is reflexive
- A relation is *symmetric* if for all u and v, uRv implies vRu
  - If u is in the same room as v, then it always true that v is in the same room as u. So the relation is symmetric
- A relation is *transitive* if for all u,v,w, uRv together with vRw implies uRw
  - If u is in the same room as v, and v is in the same room as u, then u is necessarily in the same room as w
  - So the relation is transitive
- A relation is an *equivalence* if it is reflexive, symmetric and transitive
  - Equivalence relations give rise to partitions and vice-versa
  - A partition of a set S is an exhaustive set of mutually exclusive classes such at each member of S belongs to one and only one class

Partitions of Sets

- To partition a set is to cut it up into pieces, such that every member of the set falls into one (and only one) of the pieces.
  - Exhaustive and mutually exclusive
- The pieces are called classes or colors or blocks of the partition
- Given a partition P, the class of any item u is denoted by p(u)
- We can define a relation E such that uEv iff p(u) = p(v)
  - i.e., u and v are equivalent if they belong to the same class in the partition

Equivalence Relations and Partitions

- Given a partition, the relation "is in the same block as" forms an equivalence relation
  - *Reflexivity*: an item is always in the same block as itself
  - *Symmetry*: if u is in the same block as v, then v is in the same block as u.
  - *Transitivity*: if u is in the same block as v, and w is in the same block as v, then u must be in the same block as w.

Operations

- The *converse* or *inverse* of a relation R is denoted R^{-1}.
  - For all u and v, $(u,v) \in R^{-1}$ if and only if $(v,u) \in R$
  - The converse effectively reverses the direction of the mapping
- Example
  - If R is represents "gives advice to", then uRv means u gives advice to v, and $uR^{-1}v$ indicates that v gives advice to u
- If R is symmetric, then $R = R^{-1}$

Important note: In the world of matrices, the term "inverse" and the superscript $^{-1}$ refer to a very different concept: a false cognate. The relational inverse or converse corresponds to the matrix concept of a transpose, denoted X' or X^T, and not to the matrix inverse, denoted X^{-1}.

Relational Composition

- If F and E are binary relations, then their composition $F \circ E$ is a new relation such that $(u,v) \in F \circ E$ if there exists *w* such that $(u,w) \in F$ and $(w,v) \in E$.
  - i.e., u is $F \circ E$-related to v if there exists an intermediary w such that u is F-related to w and w is E-related to v
- Example:
  - Suppose F and E are friend of and enemy of, respectively
  - u $F \circ E$ v means that u has a friend who is the enemy of v
- Easier to decode by saying it backwards:
  - What is v to u? v is the enemy of a friend of u

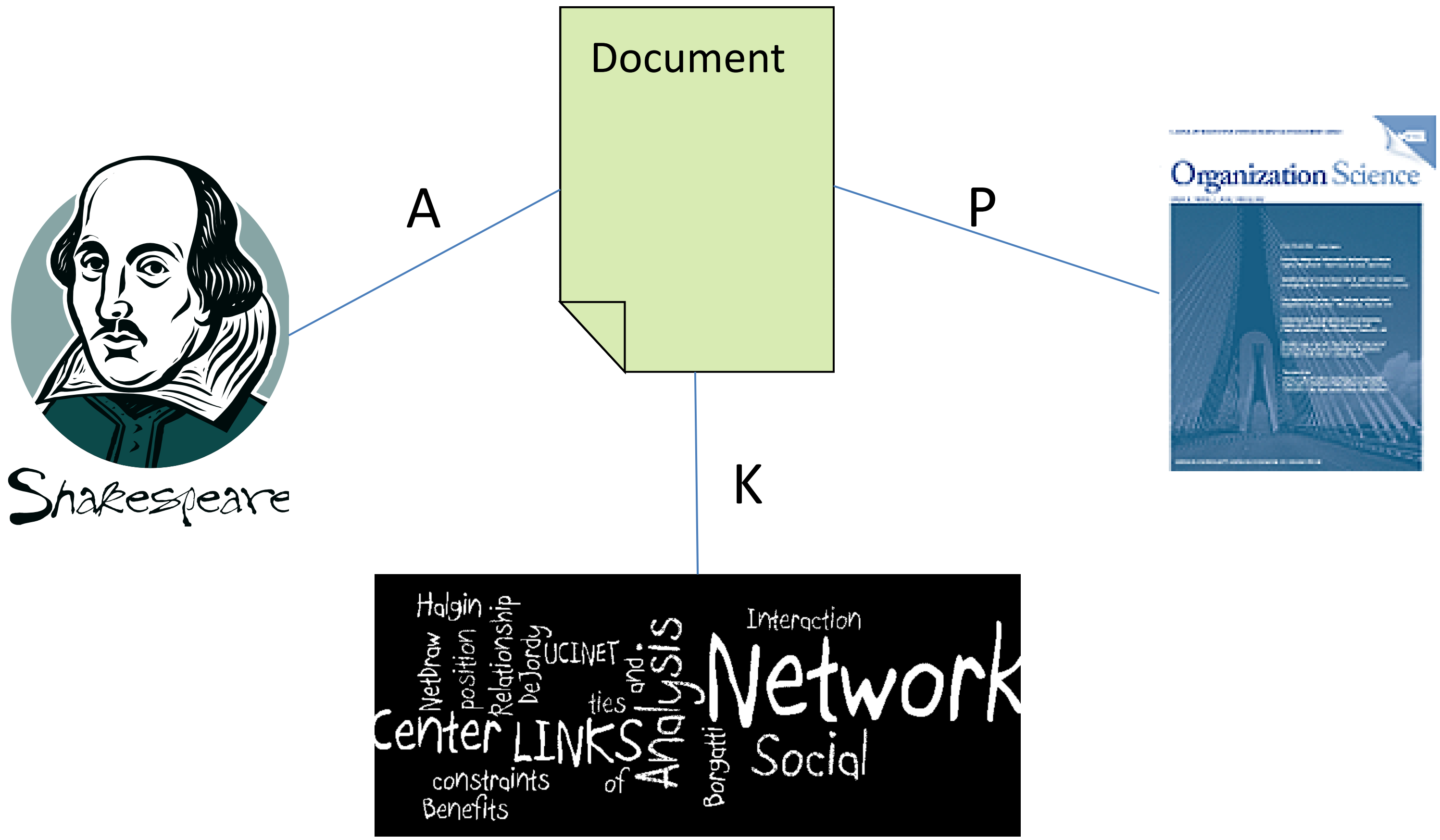
More Relational Composition

Assume F is "likes" and E is "dislikes"

- u $F \circ F$ v (or $(u,v) \in F \circ F$) means u likes someone who likes v
  - v is liked by someone who is liked by u
  - Loosely, v is a friend of a friend of u
- $(u,v) \in E \circ E$ (or u $E \circ E$ v) means u dislikes someone who dislikes v
  - v is disliked by someone who is disliked by u
  - Loosely, v is an enemy of an enemy
- u $E \circ F$ v means u dislikes someone who likes v
  - V is liked by someone who is disliked by u
  - Loosely, v is friend of an enemy of u
- Compositions are new kinds of relations, like uncle is brother of a parent

More Relational Composition

- Given these relations
  - A (authored). Relates persons → documents
  - P (published in). Relates docs → journals
  - K (has keyword). Relates docs → keywords



Compositions – cont.

A (authored). persons → documents
P (published in). docs → journals
K (has keyword). docs → keywords

AA^{-1}	if $(i,j) \in AA^{-1}$, then i authors a document that is authored by j. In short, i and j are coauthors
AP	iAPj = Person i authored a document that is published in journal j. So i has published in journal j
AK	iAKj = Person i authored a doc that has keyword j. So, i writes about topic j
$AKK^{-1}A^{-1}$	person i authored a document that has a keyword that is in a document that was authored by j. In other words, i and j write about the same topics
$AKK^{-1}A^{-1}AP$	person i authored a document that has a keyword that is in a document that was authored by someone who has published in journal j. I.e., i has written about a topic that has appeared in journal j

Relational Equations

- $F = F \circ F$ means that uFv if and only if $uF \circ Fv$
  - Friends of friends are friends, and vice versa
- $F = E \circ E$ means that uFv if and only if $uE \circ Ev$
  - Enemies of enemies are friends, and vice-versa
- $E = F \circ E = E \circ F$ means that uEv if and only if $uF \circ Ev$ and $uE \circ Fv$
  - In short, friends of enemies are enemies, and so are enemies of friends

Using relational equations, we can formally write down the expectations of balance theory

MATRIX ALGEBRA

Matrix Algebra

- In this section, we will cover:
  - Matrix Concepts, Notation & Terminologies
  - Adjacency Matrices
  - Transposes
  - Aggregations & Vectors
  - Matrix Operations
  - Boolean Algebra (and relational composition)

Matrices

- Symbolized by a capital letter, like A
- Each cell in the matrix identified by row and column subscripts: a_{ij}
  - First subscript is row, second is column

	Age	Gender	Income
Mary	32	1	90,000
Bill	50	2	45,000
John	12	2	0
Larry	20	2	8,000

A

$a_{12} = 1$

$a_{43} = 8000$

Vectors

- Each row and each column in a matrix is a vector
  - Vertical vectors are column vectors, horizontal are row vectors
- Denoted by lowercase bold letter: **y**
- Each cell in the vector identified by subscript x_i

$y_3 = 2.1$
$z_2 = 45,000$

	x	**y**	**z**
Mary	32	1	90,000
Bill	50	2	45,000
John	12	2.1	0
Larry	20	2	8,000

Ways and Modes

- Ways are the dimensions of a matrix.
- Modes are the sets of entities indexed by the ways of a matrix

	Event 1	Event 2	Event 3	Event 4
EVELYN	1	1	1	1
LAURA	1	1	1	0
THERESA	0	1	1	1
BRENDA	1	0	1	1
CHARLO	0	0	1	1
FRANCES	0	0	1	0
ELEANOR	0	0	0	0
PEARL	0	0	0	0
RUTH	0	0	0	0
VERNE	0	0	0	0
MYRNA	0	0	0	0

2-way, 2-mode

	Mary	Bill	John	Larry
Mary	0	1	0	1
Bill	1	0	0	1
John	0	1	0	0
Larry	1	0	1	0

2-way, 1-mode

2-Way, 2-Mode data

	Event 1	Event 2	Event 3	Event 4
EVELYN	1	1	1	1
LAURA	1	1	1	0
THERESA	0	1	1	1
BRENDA	1	0	1	1
CHARLO	0	0	1	1
FRANCES	0	0	1	0
ELEANOR	0	0	0	0
PEARL	0	0	0	0
RUTH	0	0	0	0
VERNE	0	0	0	0
MYRNA	0	0	0	0

Affiliations

Big 5 personality traits

ID	T1	T2	T3	T4	T5
1	0	6	6	2	0
2	0	3	3	1	0
3	2	0	0	3	0
4	6	4	4	7	4
5	3	3	3	3	3
…	…	…	..	..	..

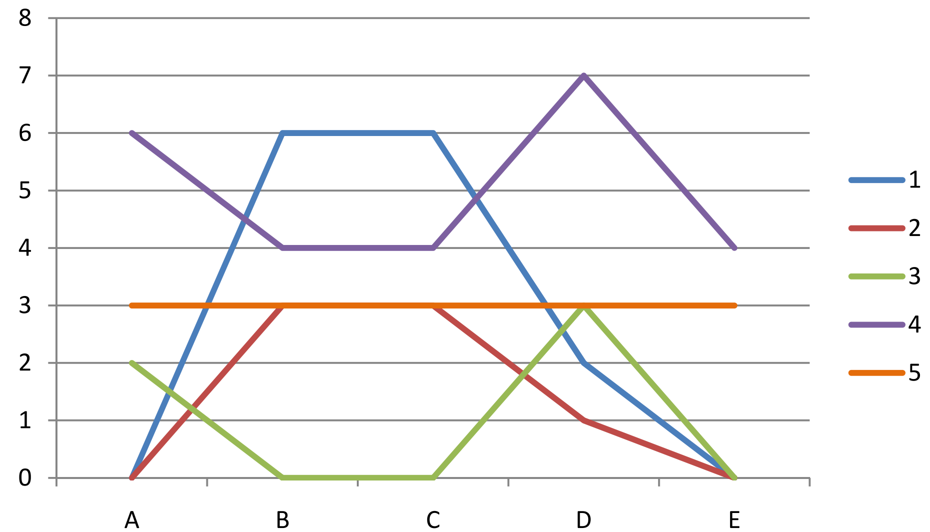
Profile data

Profiles

- Typically, we use profiles to refer to the patterns of responses across a row of a matrix, generally a 2-mode matrix.

ID	A	B	C	D	E
1	0	6	6	2	0
2	0	3	3	1	0
3	2	0	0	3	0
4	6	4	4	7	4
5	3	3	3	3	3

- We might then compare profiles across the rows to see which rows have the most similar or dissimilar profiles.
  - We can also conceive of this down the columns, as well. In fact, when we correlate variables in traditional OLS, we are actually comparing the profiles of each pair of variables across the respondents.



2-Way, 1-Mode data

Network Adjacency matrix
Friends

	Mary	Bill	John	Larry
Mary	0	1	0	1
Bill	1	0	0	1
John	0	1	0	0
Larry	1	0	1	0

		1 BOST	2 NY	3 DC	4 MIAM	5 CHIC	6 SEAT	7 SF	8 LA	9 DENV
		----	----	----	----	----	----	----	----	----
1	BOSTON	0	206	429	1504	963	2976	3095	2979	1949
2	NY	206	0	233	1308	802	2815	2934	2786	1771
3	DC	429	233	0	1075	671	2684	2799	2631	1616
4	MIAMI	1504	1308	1075	0	1329	3273	3053	2687	2037
5	CHICAGO	963	802	671	1329	0	2013	2142	2054	996
6	SEATTLE	2976	2815	2684	3273	2013	0	808	1131	1307
7	SF	3095	2934	2799	3053	2142	808	0	379	1235
8	LA	2979	2786	2631	2687	2054	1131	379	0	1059
9	DENVER	1949	1771	1616	2037	996	1307	1235	1059	0

Physical Proximity Matrix – Driving distance between cities

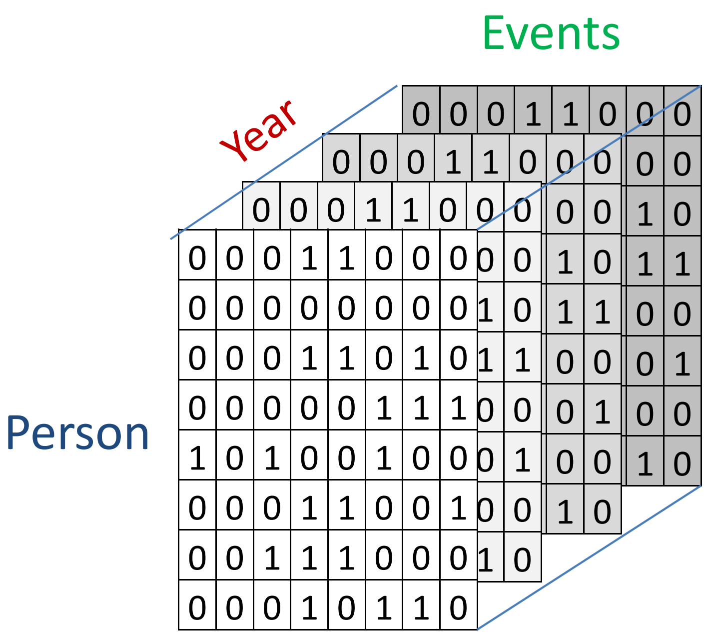
Adjacency Matrices

- Typically, the term *adjacency matrix* refers to a matrix which captures the presence or absence of a particular relationship among a set of nodes.
- As such, they generally:
  - Are square matrices (1-mode, 2-way)
  - Are dichotomous (contain only 1s and 0s)

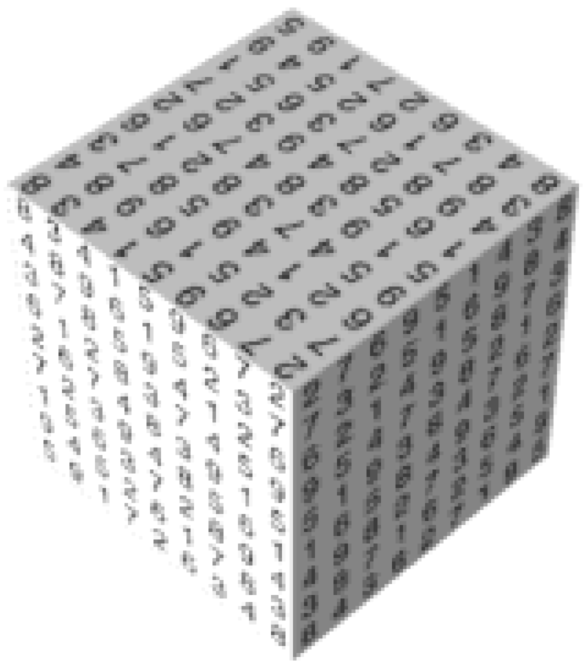
Proximity Matrices

- Proximity Matrices record “degree of proximity”.
- Proximities are usually among a single set of actor (hence, they are 1-mode), but they are not limited to 1s and 0s in the data.
- What constitutes the *proximity* is user-defined.
  - Driving distances are one form of proximities, other forms might be number of friends in common, time spent together, number of emails exchanged, or a measure of similarity in cognitive structures.
- Proximity matrices can contain either *similarity* or *distance* (or *dissimilarity*) data.
  - Similarity data, such as number of friends in common or correlations, means a larger number represents more similarity or greater proximity
  - Distance (or dissimilarity data) such as physical distance means a larger number represents more dissimilarity or less proximity

3-way data



3-way, 2-mode
Longitudinal affiliations data



3-way, 1-mode
Krackhardt-style perceptions
by each person of relations
among all pairs of persons

Aggregations and Operations

- Unary (Intra-Matrix) Operations
  - Row sums/marginals
  - Column sums/marginals
  - Matrix Sums
  - Transpose
  - Normalizations
  - Dichotomization
  - Symmetrizing
- Cellwise Binary (Inter-Matrix) Operations
  - Sum
  - Cellwise multiplication
  - Boolean Operations
- Special Binary (Inter-Matrix) Operations
  - Cross Product (Matrix Multiplication)

Summations

- Row sums

$$r_i = \sum_j x_{ij}$$

- Column sums

$$c_j = \sum_i x_{ij}$$

- Matrix sums

$$m = \sum_{i,j} x_{ij}$$

	Mary	Bill	John	Larry	Row Marginals
Mary	0	1	1	1	3
Bill	1	0	1	0	2
John	0	0	0	1	1
Larry	0	0	0	0	0
Column Marginals	1	1	2	2	6

Normalizing

- Converting to proportions
  - Rows $$x_{ij}^{*} = \frac{x_{ij}}{r_i}$$ where r_i gives the sum of row i
  - Columns $$x_{ij}^{*} = \frac{x_{ij}}{c_j}$$

	Mary	Bill	John	Larry	Row Sums
Mary	0	1	1	1	3
Bill	1	0	1	0	2
John	0	0	0	1	1
Larry	0	0	0	0	0
Column Marginals	1	1	2	2	6

	Mary	Bill	John	Larry	Row sums
Mary	0	.33	.33	.33	1
Bill	.5	0	.5	0	1
John	0	0	0	1	1
Larry					
Column Marginals	.5	.33	.83	1.33	3

Normalizing

- Converting to z-scores (standardizing)
  - Columns

$$x_{ij}^{*} = \frac{x_{ij} - u_j}{\sigma_j}$$

where u_j gives the mean of column j, and σ_j is the std deviation of column j

	Var 1	Var 2	Var 3	Var 4
Mary	3	20	25	10
Bill	1	55	15	45
John	0	32	10	22
Larry	2	2	20	-8
Mean	1.5	27.3	17.5	17.3
Std Dev	1.1	19.3	5.6	19.3

	Var 1	Var 2	Var 3	Var 4
Mary	1.34	-0.38	1.34	-0.38
Bill	-0.45	1.44	-0.45	1.44
John	-1.34	0.25	-1.34	0.25
Larry	0.45	-1.31	0.45	-1.31
Mean	0.00	0.00	0.00	0.00
Std Dev	1.00	1.00	1.00	1.00

Transposes

- The transpose of a matrix is the matrix flipped on its side.
  – The rows become columns and the columns become rows
  – So the transpose of an m by n matrix is an n by m matrix.

- Here is the matrix presented on the last side, and its transpose
  – The transpose of matrix M is indicated by M’ or M^T

	A	B	C	D	E
1	0	6	6	2	0
2	0	3	3	1	0
3	2	0	0	3	0
4	6	4	4	7	4
5	3	3	3	3	3

Matrix M

	1	2	3	4	5
A	0	0	2	6	3
B	6	3	0	4	3
C	6	3	0	4	3
D	2	1	3	7	3
E	0	0	0	4	3

Its transpose, M’

Transpose (Another Example)

- Given Matrix M, swap the rows and columns to make Matrix M^T

M	Tennis	Football	Rugby	Golf
Mike	0	0	1	0
Ron	0	1	1	0
Pat	0	0	0	1
Bill	1	1	1	1
Joe	0	0	0	0
Rich	0	1	1	1
Peg	1	1	0	1

$\mathbf{M^T}$	Mike	Ron	Pat	Bill	Joe	Rich	Peg
Tennis	0	0	0	1	0	0	1
Football	0	1	0	1	0	1	1
Rugby	1	1	0	1	0	1	0
Golf	0	0	1	1	0	1	1

Dichotomizing

- X is a valued matrix, say 1 to 10 rating of strength of tie
- Construct a matrix Y of ones and zeros so that
  - $y_{ij} = 1$ if $x_{ij} > 5$, and $y_{ij} = 0$ otherwise

X

	EVE	LAU	THE	BRE	CHA
EVELYN	8	6	7	6	3
LAURA	6	7	6	6	3
THERESA	7	6	8	6	4
BRENDA	6	6	6	7	4
CHARLOTTE	3	3	4	4	4

Y

	EVE	LAU	THE	BRE	CHA
EVELYN	1	1	1	1	0
LAURA	1	1	1	1	0
THERESA	1	1	1	1	0
BRENDA	1	1	1	1	0
CHARLOTTE	0	0	0	0	0

$x_{ij} > 5$

Symmetrizing

- When matrix is not symmetric, i.e., $x_{ij} \neq x_{ji}$
- Symmetrize various ways. Set y_{ij} and y_{ji} to:
  - Maximum(x_{ij}, x_{ji}) {union rule}
  - Minimum (x_{ij}, x_{ji}) {intersection rule}
  - Average: $(x_{ij} + x_{ji})/2$
  - Lowerhalf: choose x_{ij} when $i > j$ and x_{ji} otherwise
  - etc

Symmetrizing Example

- X is non-symmetric (and happens to be valued)
- Construct matrix Y such that y_{ij} (and y_{ji}) = maximum of x_{ij} and x_{ji}

X

	ROM	BON	AMB	BER	PET	LOU
ROMUL_10	0	1	1	0	3	0
BONAVEN_5	0	0	1	0	3	2
AMBROSE_9	0	1	0	0	0	0
BERTH_6	0	1	2	0	3	0
PETER_4	0	3	0	1	0	2
LOUIS_11	0	2	0	0	0	0

	ROM	BON	AMB	BER	PET	LOU
ROMUL_10	0	1	1	0	3	0
BONAVEN_5	1	0	1	1	3	2
AMBROSE_9	1	1	0	2	0	0
BERTH_6	0	1	2	0	3	0
PETER_4	3	3	0	3	0	2
LOUIS_11	0	2	0	0	2	0

Symmetrized by Maximum

Cellwise Binary Operators

- Sum (Addition)

  $C = A + B$ where $c_{ij} = a_{ij} + b_{ij}$

- Cellwise (Element) Multiplication

  $C = A * B$ where $c_{ij} = a_{ij} * b_{ij}$

- Boolean operations

  $C = A \wedge B$ (Logical And) where $c_{ij} = a_{ij} \wedge b_{ij}$

  $C = A \vee B$ (Logical Or) where $c_{ij} = a_{ij} \vee b_{ij}$

Matrix Multiplication

- Notation: C = AB
- Definition: $$c_{ij} = \sum_k a_{ik} b_{kj}$$

Note: matrix products are not generally commutative. i.e., AB does not usually equal BA

- Example:

	Mary	Bill	John	Larry
Mary	0	1	1	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	0	0	0

A

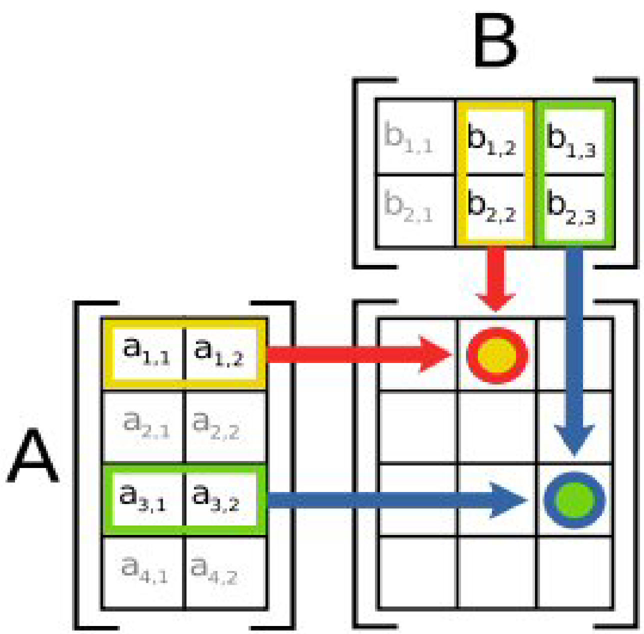
	Mary	Bill	John	Larry
Mary	0	0	1	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	1	0	0

B

	Mary	Bill	John	Larry
Mary	1	1	1	1
Bill	0	0	1	2
John	0	1	0	0
Larry	0	0	0	0

C=AB

Matrix Multiplication



- C = AB or C = A x B
  - Only possible when the number of columns in A is the same as the number of rows in B, as in ${}_mA_k$ and ${}_kB_n$
  - These are said to be <u>conformable</u>
  - Produces ${}_mC_n$
- It is calculated as:

  $\mathbf{c_{ij} = \Sigma\, a_{ik} * b_{kj}}$ **for all k**

$$\begin{bmatrix} 1 & 0 & 2 \\ -1 & 3 & 1 \end{bmatrix} \cdot \begin{bmatrix} 3 & 1 \\ 2 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 \times 3 + 0 \times 2 + 2 \times 1 & 1 \times 1 + 0 \times 1 + 2 \times 0 \\ -1 \times 3 + 3 \times 2 + 1 \times 1 & -1 \times 1 + 3 \times 1 + 1 \times 0 \end{bmatrix} = \begin{bmatrix} 5 & 1 \\ 4 & 2 \end{bmatrix}$$

A Matrix Product Example

Skills	Math	Verbal	Analytic
Kev	1.00	.75	.80
Jeff	.80	.80	.90
Lisa	.75	.60	.75
Kim	.80	1.00	.85

Items	Q1	Q2	Q3	Q4
Math	.50	.75	0	.1
Verbal	.10	0	.9	.1
Analytic	.40	.25	.1	.8

- Given a Skills and Items matrix calculate the "affinity" that each person has for each question
- Kev for Question 1 is:

  = 1.00 * .5 + .75* .1 + .80 * .40

  = .5 + .075 + .32 = **0.895**
- Lisa for Question 3 is:

  = .75 * .0 + .60* .90 + .75 * .1

  = .0 + .54 + .075 = **0.615**

Affin	Q1	Q2	Q3	Q4
Kev	0.895	0.95	0.755	0.815
Jeff	0.840	0.825	0.810	0.880
Lisa	0.735	0.75	0.615	0.735
Kim	0.840	0.813	0.985	0.860

Matrix Inverse and Identity

- The inverse of a matrix X is a Matrix X^{-1} such that $XX^{-1} = I$, where I is the identity matrix
- Inverse matrices can be very useful for solving matrix equations that underlie some network algorithms

X

1	0	-2
4	1	0
1	1	7

X^{-1}

7	-2	2
-28	9	-8
3	-1	1

=

I

1	0	0
0	1	0
0	0	1

Note:

- $(XX^{-1} = X^{-1}X = I)$
- Non square matrices do not have an inverse*

Boolean matrix multiplication

- Values can be 0 or 1 for all matrices
- Products are dichotomized

Would have been a 2 in regular matrix multiplication (refers to the Bill–Larry cell of AB)

	Mary	Bill	John	Larry
Mary	0	1	0	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	0	0	0

A

	Mary	Bill	John	Larry
Mary	0	0	1	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	1	0	0

B

	Mary	Bill	John	Larry
Mary	1	1	1	0
Bill	0	0	0	1
John	0	1	0	0
Larry	0	0	0	0

AB

Relational Composition

- If we represent binary relations as binary adjacency matrices, boolean matrix products correspond to relational composition
  - $F \circ E$ corresponds to FE

Likes

	Mary	Bill	John	Larry
Mary	0	1	0	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	0	0	0

F

Has conflicts with

	Mary	Bill	John	Larry
Mary	0	0	1	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	1	0	0

E

Likes someone who has conflicts with

	Mary	Bill	John	Larry
Mary	1	1	1	0
Bill	0	0	0	1
John	0	1	0	0
Larry	0	0	0	0

FE

Products of matrices & their transposes

- X'X = pre-multiplying X by its transpose

$$(X'X)_{ij} = \sum_k a_{ki} b_{kj}$$

- Computes sums of products of each pair of columns (cross-products)
- The basis for most similarity measures

	1	2	3	4
Mary	0	1	1	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	0	0	0

→

	1	2	3	4
1	1	0	1	0
2	0	1	1	1
3	1	1	2	1
4	0	1	1	2

Products of matrices & their transposes

- XX' = product of matrix X by its transpose

$$(XX')_{ij} = \sum_k a_{ik} b_{jk}$$

- Computes sums of products of each pair of rows (cross-products)
- Similarities among rows

	1	2	3	4
Mary	0	1	1	1
Bill	1	0	1	0
John	0	0	0	1
Larry	0	0	0	0

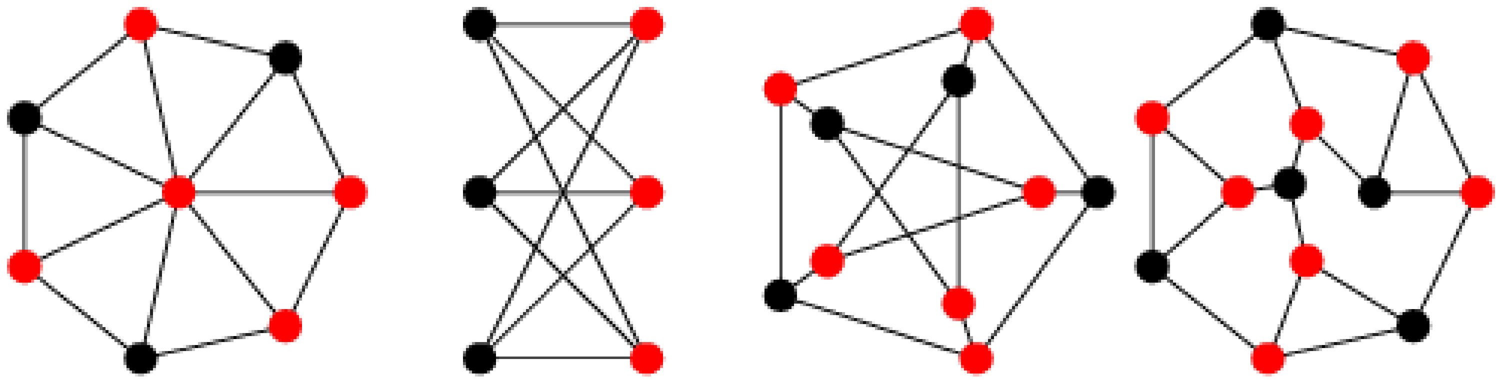
	Mary	Bill	John	Larry
Mary	3	1	1	0
Bill	1	2	0	0
John	1	0	1	0
Larry	0	0	0	0

Multiplying a matrix by its transpose

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14
EVELYN	1	1	1	1	1	1	0	1	1	0	0	0	0	0
LAURA	1	1	1	0	1	1	1	1	0	0	0	0	0	0
THERESA	0	1	1	1	1	1	1	1	1	0	0	0	0	0
BRENDA	1	0	1	1	1	1	1	1	0	0	0	0	0	0
CHARLOTTE	0	0	1	1	1	0	1	0	0	0	0	0	0	0
FRANCES	0	0	1	0	1	1	0	1	0	0	0	0	0	0
ELEANOR	0	0	0	0	1	1	1	1	0	0	0	0	0	0
PEARL	0	0	0	0	0	1	0	1	1	0	0	0	0	0
RUTH	0	0	0	0	1	0	1	1	1	0	0	0	0	0
VERNE	0	0	0	0	0	0	1	1	1	0	0	1	0	0
MYRNA	0	0	0	0	0	0	0	1	1	1	0	1	0	0
KATHERINE	0	0	0	0	0	0	0	1	1	1	0	1	1	1
SYLVIA	0	0	0	0	0	0	1	1	1	1	0	1	1	1
NORA	0	0	0	0	0	1	1	0	1	1	1	1	1	1
HELEN	0	0	0	0	0	0	1	1	0	1	1	1	0	0
DOROTHY	0	0	0	0	0	0	0	1	1	0	0	0	0	0
OLIVIA	0	0	0	0	0	0	0	0	1	0	1	0	0	0
FLORA	0	0	0	0	0	0	0	0	1	0	1	0	0	0

	EV	LA	TH	BR	CH	FR	EL	PE	RU	VE	MY	KA	SY	NO	HE	DO	OL	FL
E1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E3	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
E4	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
E5	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
E6	1	1	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	0
E7	0	1	1	1	1	0	1	0	1	1	0	0	1	1	1	0	0	0
E8	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	0	0
E9	1	0	1	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1
E10	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0
E11	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1
E12	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0
E13	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
E14	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0

	EVE	LAU	THE	BRE	CHA	FRA	ELE	PEA	RUT	VER	MYR	KAT	SYL	NOR	HEL	DOR	OLI	FLO
EVELYN	8	6	7	6	3	4	3	3	3	2	2	2	2	2	1	2	1	1
LAURA	6	7	6	6	3	4	4	2	3	2	1	1	2	2	2	1	0	0
THERESA	7	6	8	6	4	4	4	3	4	3	2	2	3	3	2	2	1	1
BRENDA	6	6	6	7	4	4	4	2	3	2	1	1	2	2	2	1	0	0
CHARLOTTE	3	3	4	4	4	2	2	0	2	1	0	0	1	1	1	0	0	0
FRANCES	4	4	4	4	2	4	3	2	2	1	1	1	1	1	1	1	0	0
ELEANOR	3	4	4	4	2	3	4	2	3	2	1	1	2	2	2	1	0	0
PEARL	3	2	3	2	0	2	2	3	2	2	2	2	2	2	1	2	1	1
RUTH	3	3	4	3	2	2	3	2	4	3	2	2	3	2	2	2	1	1
VERNE	2	2	3	2	1	1	2	2	3	4	3	3	4	3	3	2	1	1
MYRNA	2	1	2	1	0	1	1	2	2	3	4	4	4	3	3	2	1	1
KATHERINE	2	1	2	1	0	1	1	2	2	3	4	6	6	5	3	2	1	1
SYLVIA	2	2	3	2	1	1	2	2	3	4	4	6	7	6	4	2	1	1
NORA	2	2	3	2	1	1	2	2	2	3	3	5	6	8	4	1	2	2
HELEN	1	2	2	2	1	1	2	1	2	3	3	3	4	4	5	1	1	1
DOROTHY	2	1	2	1	0	1	1	2	2	2	2	2	2	1	1	2	1	1
OLIVIA	1	0	1	0	0	0	0	1	1	1	1	1	1	2	1	1	2	2
FLORA	1	0	1	0	0	0	0	1	1	1	1	1	1	2	1	1	2	2

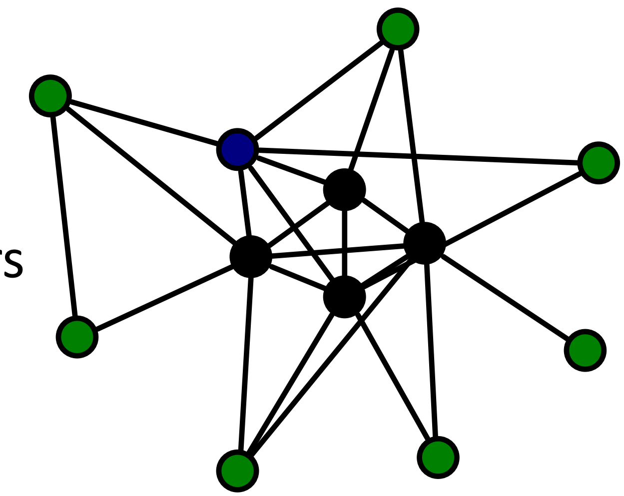


Graph Theoretic Concepts

- In this section we will cover:
  - Definitions
  - Terminology
  - Adjacency
  - Density concepts
    - E.g, Completeness
  - Walks, trails, paths
  - Cycles, Trees
  - Reachability/Connectedness
    - Connectivity, flows
  - Isolates, Pendants, Centers
  - Components, bi-components
  - Walk Lengths, distance
    - Geodesic distance
  - Independent paths
  - Cutpoints, bridges

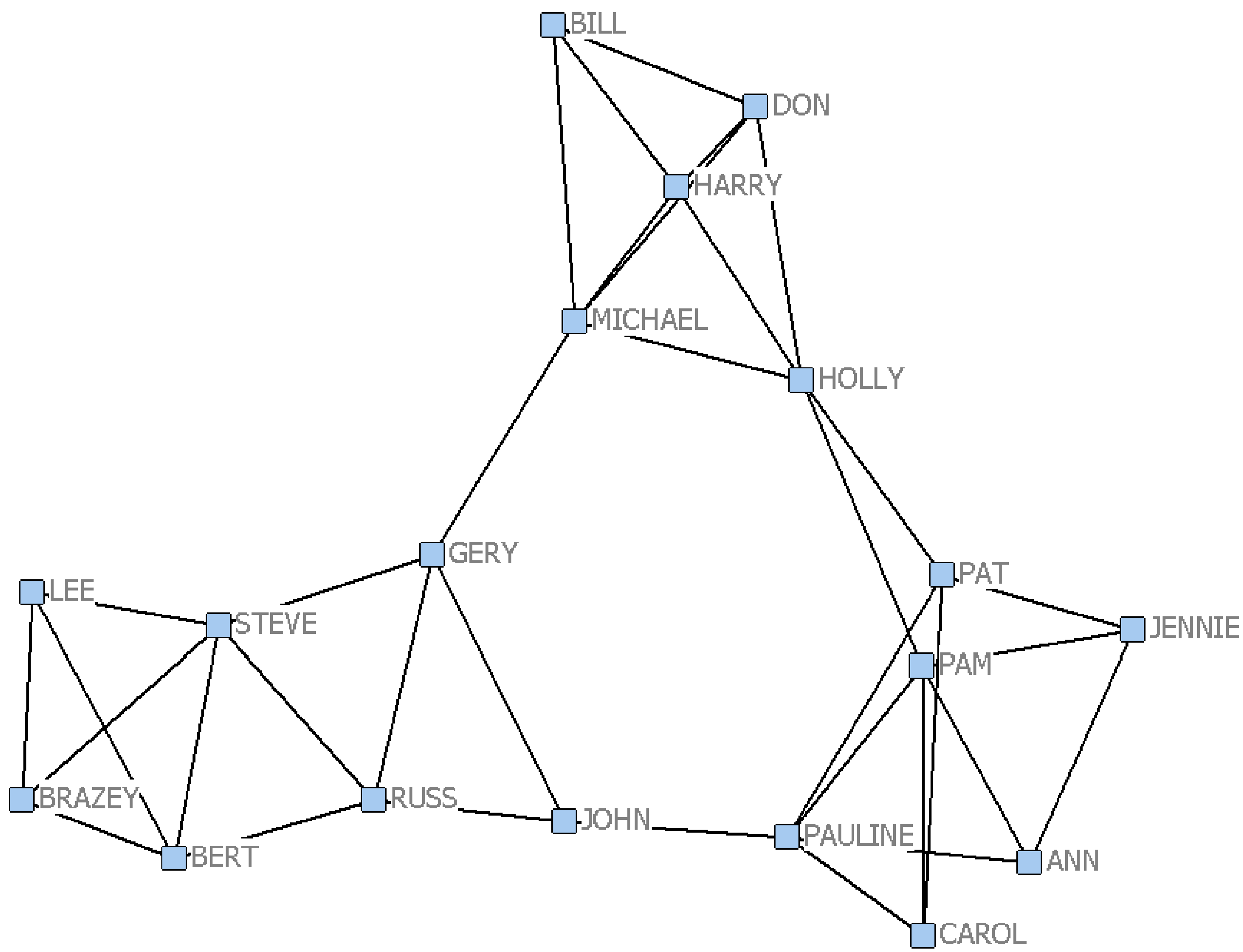
Undirected Graphs

- An undirected graph G(V,E) (often referred to simply as a graph) consists of …
  - Set of nodes|vertices V representing actors
  - Set of lines|links|edges E representing ties among pairs of actors
    - An edge is an unordered pair of nodes (u,v)
    - Nodes u and v adjacent if $(u,v) \in E$
    - So E is subset of set of all pairs of nodes



- Drawn without arrow heads
  - Sometimes with dual arrow heads
- Used to represent logically symmetric social relations
  - In communication with; attending same meeting as

Graphical representation of a graph

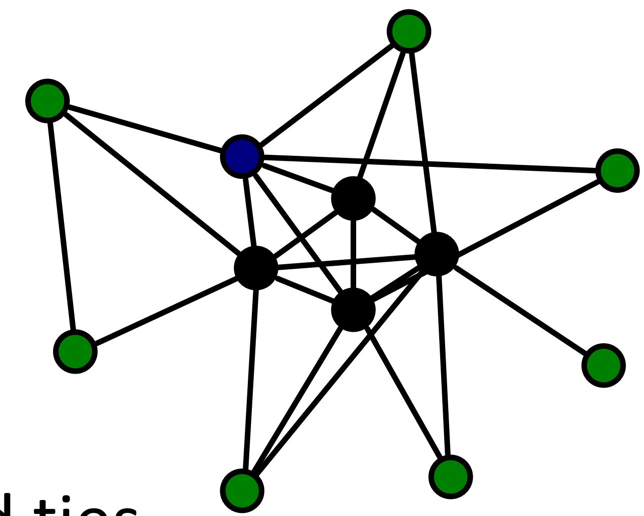


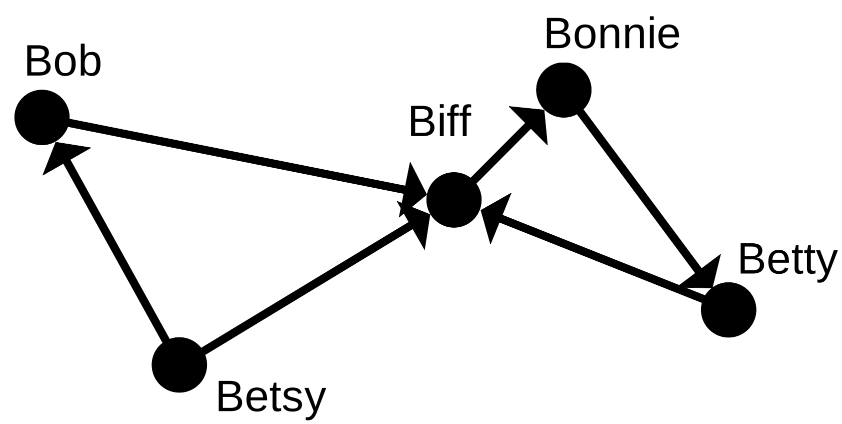
Adjacency matrix of a graph

		1 HO	2 BR	3 CA	4 PA	5 PA	6 JE	7 PA	8 AN	9 MI	10 BI	11 LE	12 DO	13 JO	14 HA	15 GE	16 ST	17 BE	18 RU
1	HOLLY	0	0	0	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0
2	BRAZEY	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0
3	CAROL	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
4	PAM	1	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
5	PAT	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
6	JENNIE	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0
7	PAULINE	0	0	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0
8	ANN	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0
9	MICHAEL	1	0	0	0	0	0	0	0	0	1	0	1	0	1	1	0	0	0
10	BILL	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0
11	LEE	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
12	DON	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0
13	JOHN	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1
14	HARRY	1	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0
15	GERY	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	1
16	STEVE	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1
17	BERT	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1
18	RUSS	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0

Directed vs. Undirected Ties

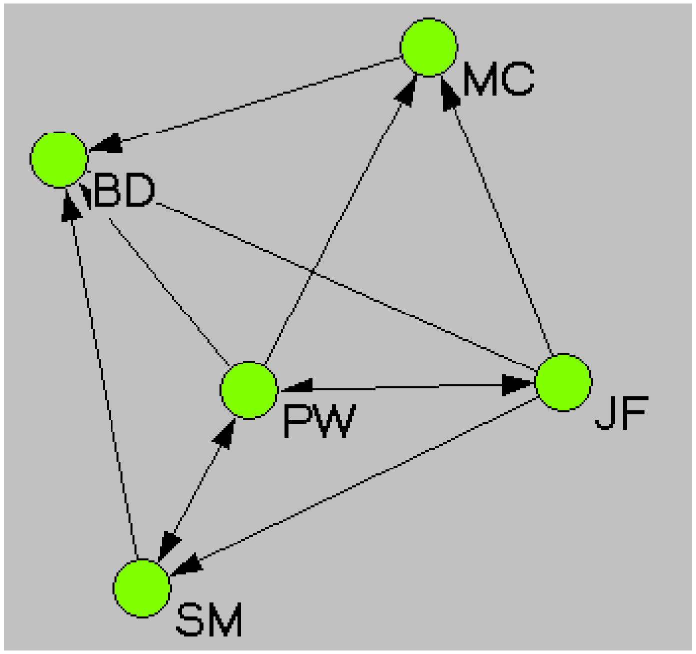
- Undirected relations
  - Attended meeting with
  - Communicates daily with
- Directed relations
  - Lent money to
- Logically vs empirically directed ties
  - Empirically, even un-directed relations can be non-symmetric due to measurement error





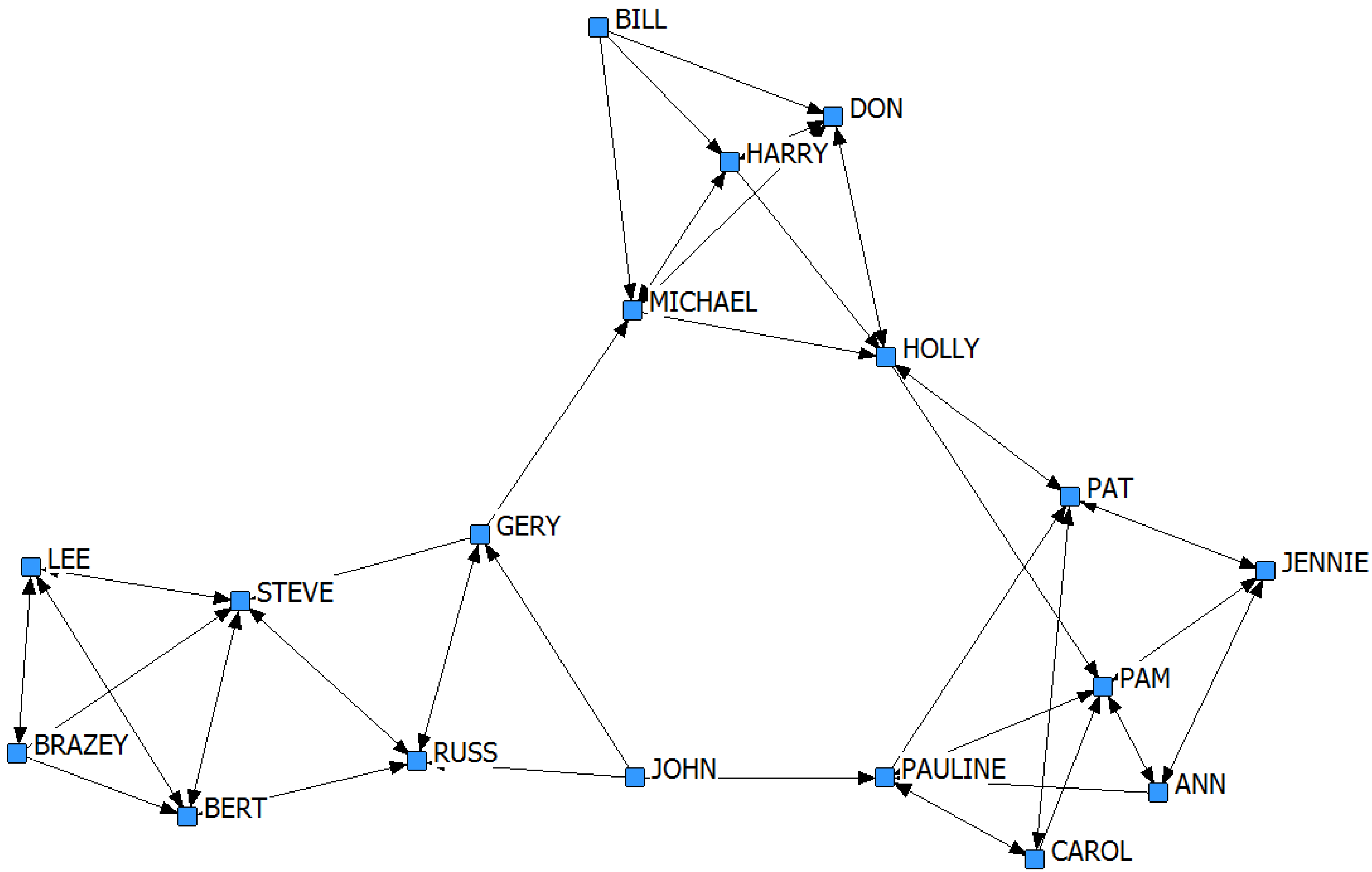
Directed Graphs (Digraphs)

- Digraph G(V,E) consists of …
  - Set of nodes V
  - Set of directed arcs E
    - An arc is an ordered pair of nodes (u,v)
    - (u,v) $\in$ E indicates u sends arc to v
    - (u,v) $\in$ E does <u>not</u> imply that (v,u) $\in$ E



- Ties drawn with arrow heads, which can be in both directions
- Represent logically non-symmetric or anti-symmetric social relations
  - Lends money to

Graphical representation of a digraph



Adjacency matrix of a digraph

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
1	HOLLY	1	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0
2	BRAZEY	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0
3	CAROL	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
4	PAM	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0
5	PAT	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
6	JENNIE	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
7	PAULINE	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
8	ANN	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0
9	MICHAEL	1	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0
10	BILL	0	0	0	0	0	0	0	0	1	1	0	1	0	1	0	0	0	0
11	LEE	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0
12	DON	1	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0
13	JOHN	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	1
14	HARRY	1	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0
15	GERY	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1
16	STEVE	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1
17	BERT	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1
18	RUSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1

Transpose Adjacency matrix

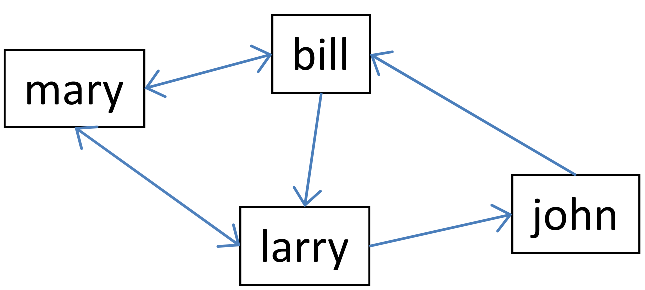
- Interchanging rows/columns of adjacency matrix effectively reverses the direction of ties

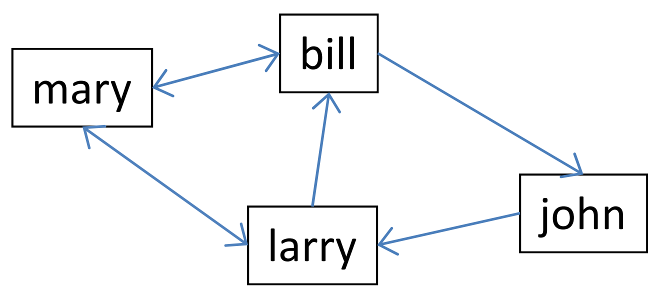
	Mary	Bill	John	Larry
Mary	0	1	0	1
Bill	1	0	0	1
John	0	1	0	0
Larry	1	0	1	0

Gives money to

	Mary	Bill	John	Larry
Mary	0	1	0	1
Bill	1	0	1	0
John	0	0	0	1
Larry	1	1	0	0

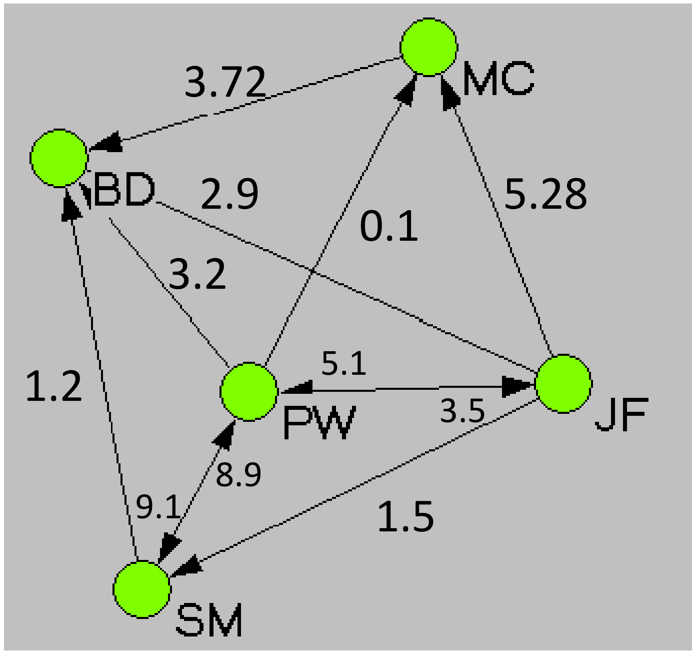
Gets money from





Valued Digraphs (Vigraphs)

- A valued digraph G(V,E,W) consists of …
  - Set of nodes V
  - Set of directed arcs E
    - An arc is an ordered pair of nodes (u,v)
    - $(u,v) \in E$ indicates u sends arc to v
    - $(u,v) \in E$ does not imply that $(v,u) \in E$
  - Mapping W of arcs to real values
- Values can represent such things as
  - Strength of relationship
  - Information capacity of tie
  - Rates of flow or traffic across tie
  - Distances between nodes
  - Probabilities of passing on information
  - Frequency of interaction



Valued Adjacency Matrix

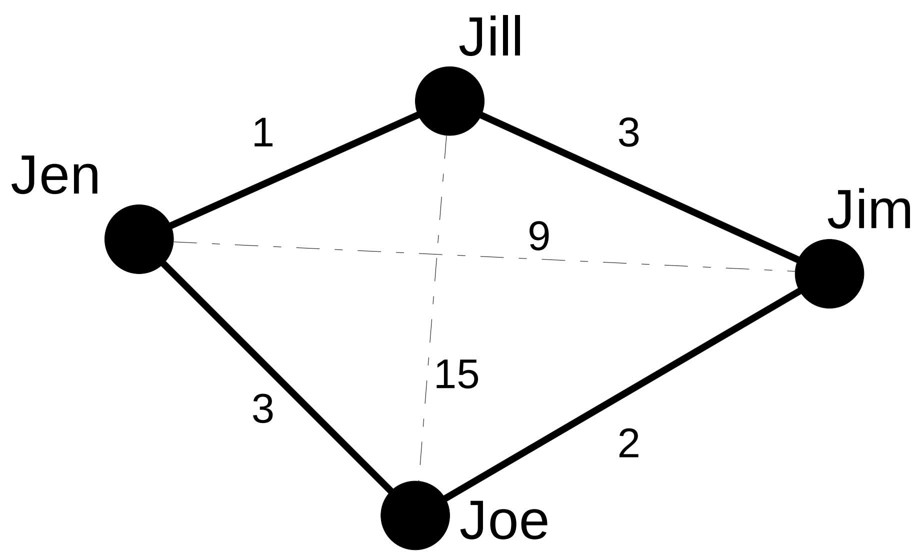
Dichotomized

	Jim	Jill	Jen	Joe
Jim	-	1	0	1
Jill	1	-	1	0
Jen	0	1	-	1
Joe	1	0	1	-

Distances btw offices

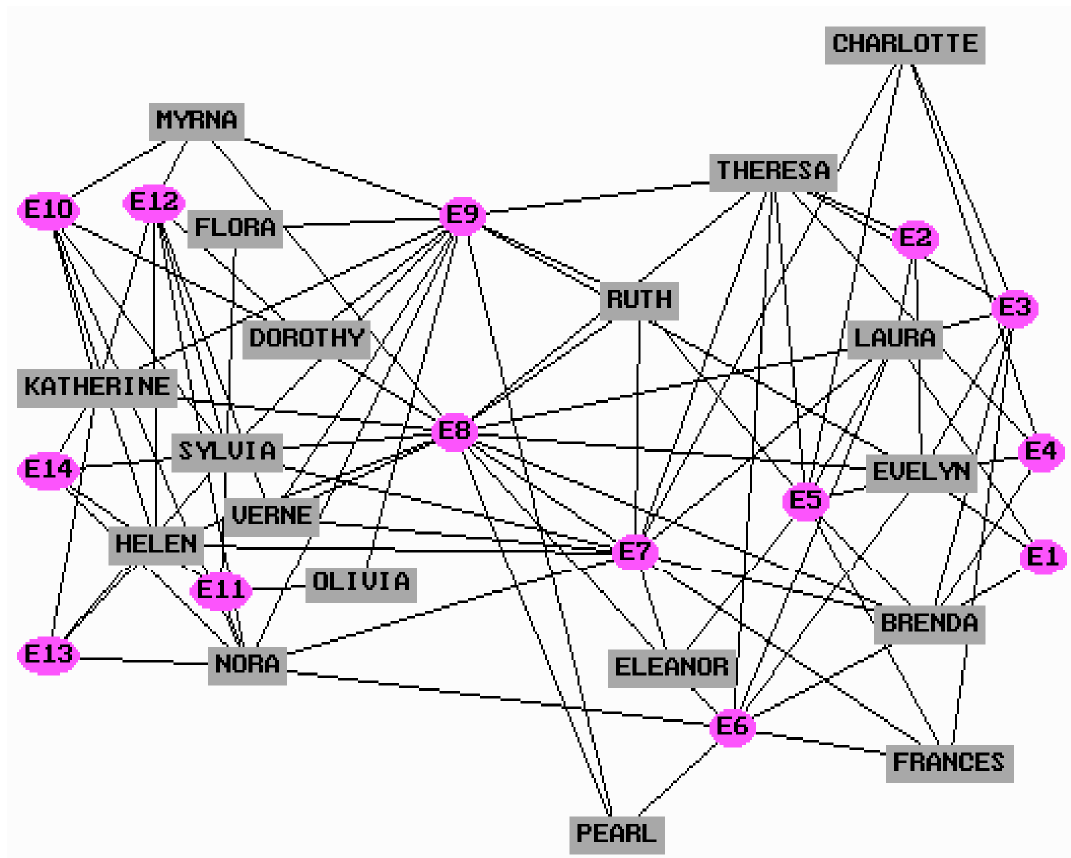
	Jim	Jill	Jen	Joe
Jim	-	3	9	2
Jill	3	-	1	15
Jen	9	1	-	3
Joe	2	15	3	-

- The diagram below uses solid lines to represent the adjacency matrix, while the numbers along the solid line (and dotted lines where necessary) represent the proximity matrix.
- In this particular case, one can derive the adjacency matrix by dichotomizing the proximity matrix on a condition of p_{ij} <= 3.

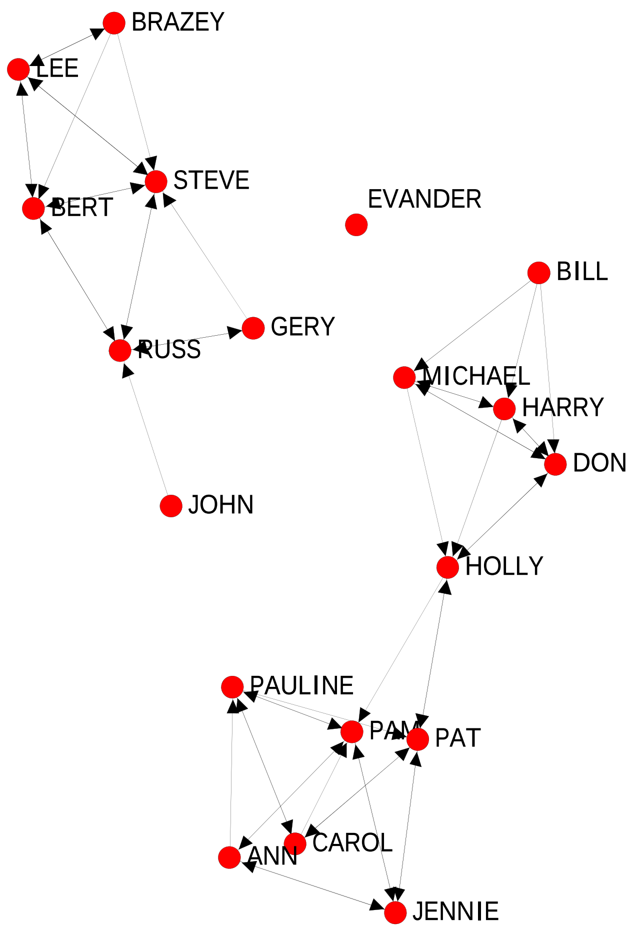


Bipartite graphs

- Used to represent 2-mode data
- Nodes can be partitioned into two sets (corresponding to modes)
- Ties occur only between sets, not within



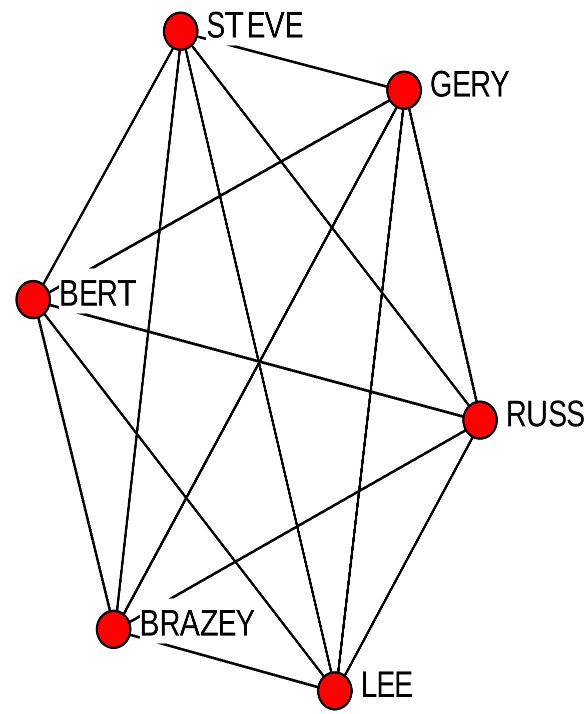
Node-related concepts



- **Degree**
  - The number of ties incident upon a node
  - In a digraph, we have indegree (number of arcs to a node) and outdegree (number of arcs from a node)
- **Pendant**
  - A node connected to a component through only one edge or arc
    - A node with degree 1
    - Example: John
- **Isolate**
  - A node which is a component on its own
    - E.g., Evander

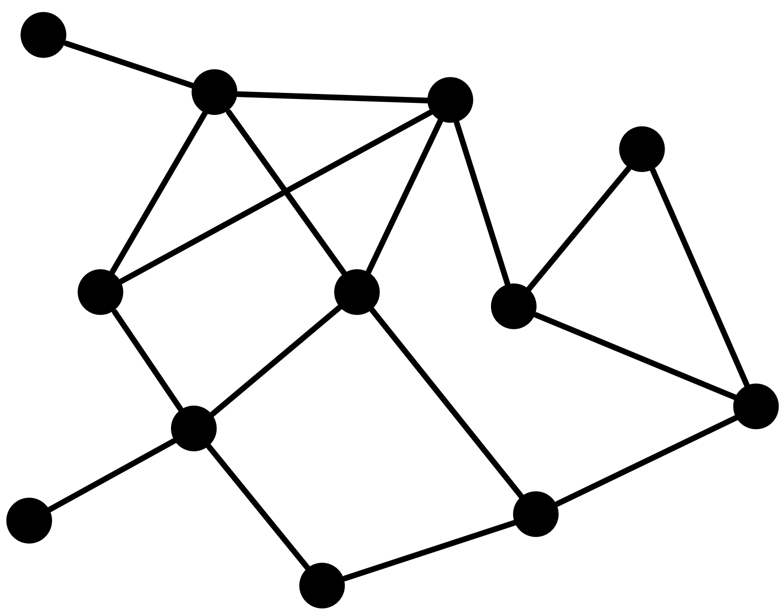
Density and Completeness

- A graph is *complete* if all possible edges are present.
- The *density* of a graph is the number of edges present divided by the number that could have been

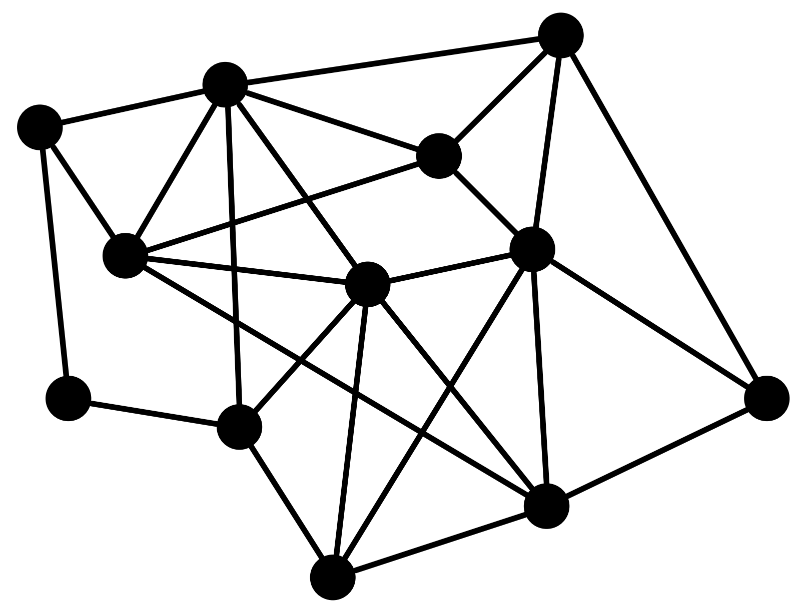


Density

- Number of ties, expressed as percentage of the number of ordered/unordered pairs



Low Density (25%)
Avg. Dist. = 2.27



High Density (39%)
Avg. Dist. = 1.76

Density

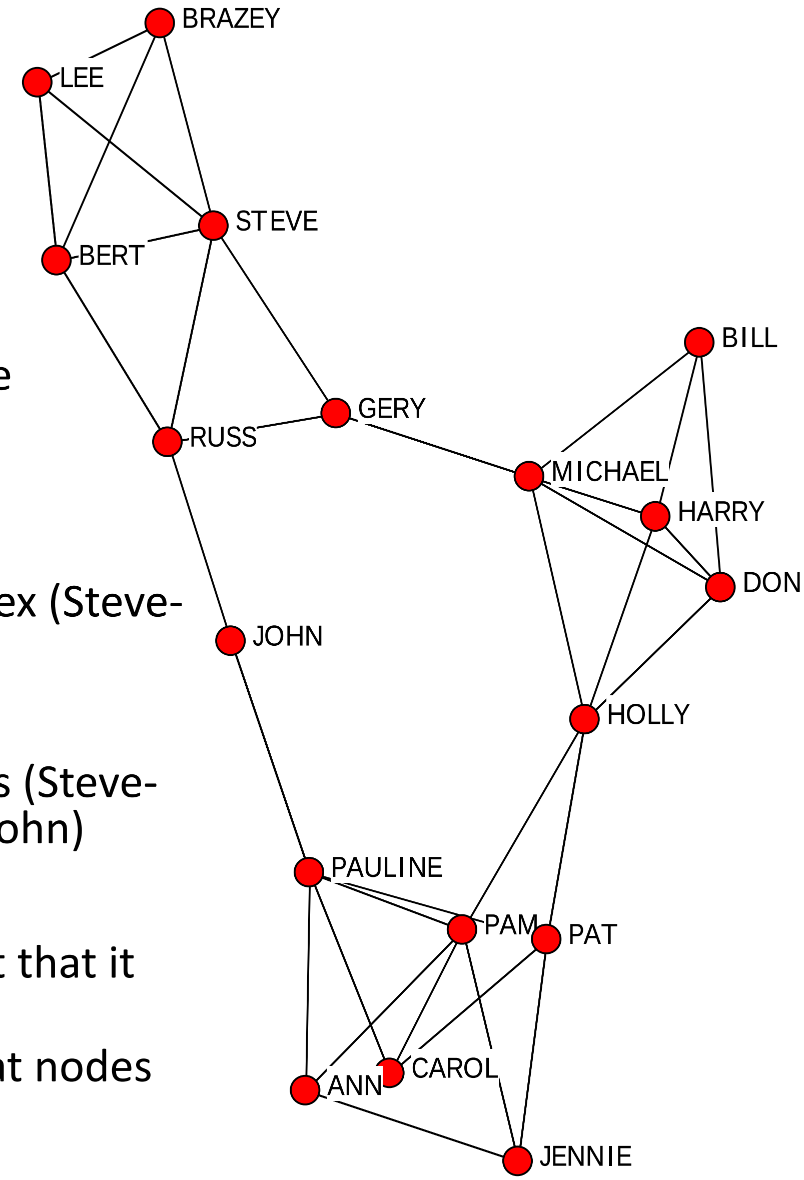
Number of ties divided by number possible

	Ties to Self Allowed	No ties to self
Undirected	$=\frac{T}{n^2/2}$	$=\frac{T}{n(n-1)/2}$
Directed	$=\frac{T}{n^2}$	$=\frac{T}{n(n-1)}$

T = number of ties in network
n = number of nodes

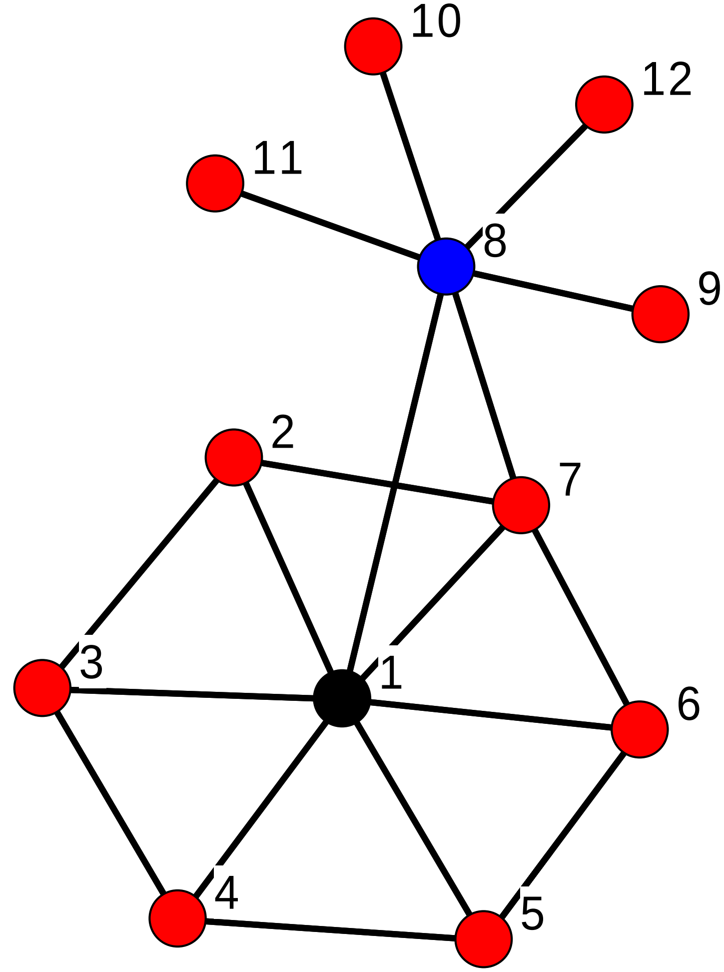
Graph traversals

- Walk
  - Any unrestricted traversing of vertices across edges (Russ-Steve-Bert-Lee-Steve)
- Trail
  - A walk restricted by not repeating an edge or arc, although vertices can be revisited (Steve-Bert-Lee-Steve-Russ)
- Path
  - A trail restricted by not revisiting any vertex (Steve-Lee-Bert-Russ)
- Geodesic Path
  - The shortest path(s) between two vertices (Steve-Russ-John is shortest path from Steve to John)
- Cycle
  - A cycle is in all ways just like a path except that it ends where it begins
  - Aside from endpoints, cycles do not repeat nodes
  - E.g. Brazey-Lee-Bert-Steve-Brazey



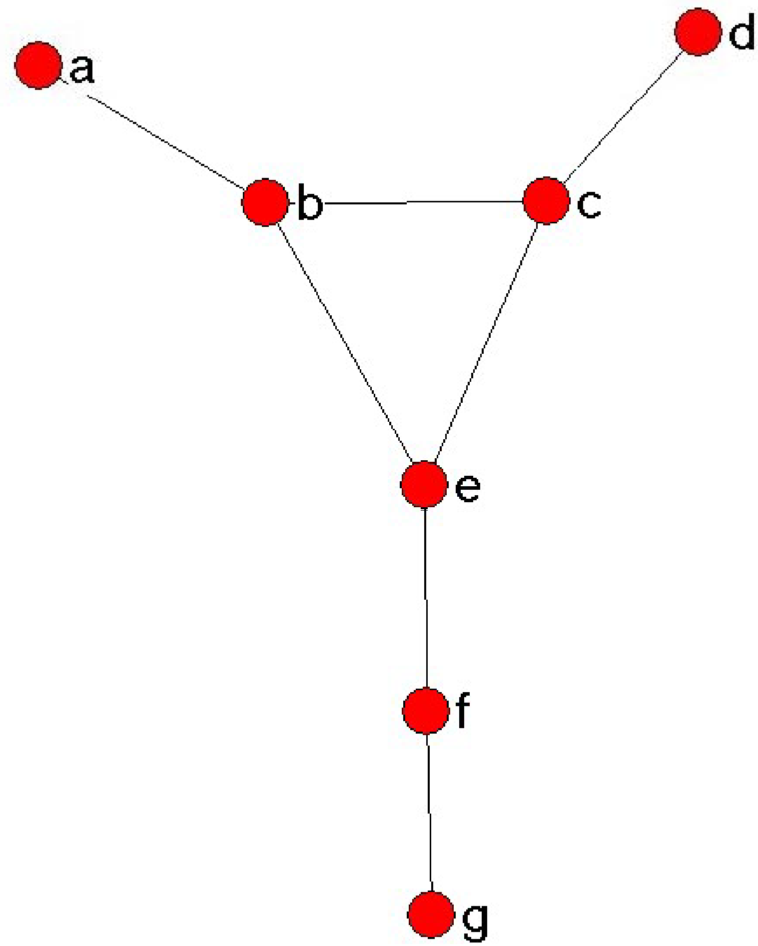
Length & Distance

- Length of a path (or any walk) is the number of links it has
- The **Geodesic Distance** (aka graph-theoretic distance) between two nodes is the length of the shortest path
  - Distance from 5 to 8 is 2, because the shortest path (5-1-8) has two links



Geodesic Distance Matrix

	a	b	c	d	e	f	g
a	0	1	2	3	2	3	4
b	1	0	1	2	1	2	3
c	2	1	0	1	1	2	3
d	3	2	1	0	2	3	4
e	2	1	1	2	0	1	2
f	3	2	2	3	1	0	1
g	4	3	3	4	2	1	0

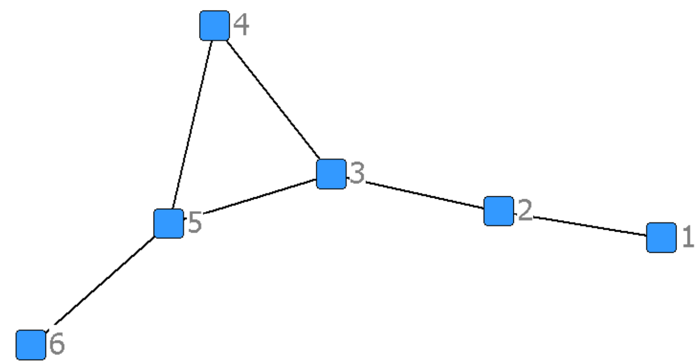


Powers of the adjacency matrix

- If you multiply an adjacency matrix X by itself, you get XX or X^2
- A given cell x^2_{ij} gives the number of walks from node i to node j of length 2
- More generally, the cells of X^k give the number of walks of length exactly *k* from each node to each other

Matrix powers example

Note that shortest path from 1 to 5 is three links, so $x_{1,5} = 0$ until we get to X^3



	1	2	3	4	5	6
1	0	1	0	0	0	0
2	1	0	1	0	0	0
3	0	1	0	1	1	0
4	0	0	1	0	1	0
5	0	0	1	1	0	1
6	0	0	0	0	1	0

X

	1	2	3	4	5	6
1	1	0	1	0	0	0
2	0	2	0	1	1	0
3	1	0	3	1	1	1
4	0	1	1	2	1	1
5	0	1	1	1	3	0
6	0	0	1	1	0	1

X^2

	1	2	3	4	5	6
1	0	2	0	1	1	0
2	2	0	4	1	1	1
3	0	4	2	4	5	1
4	1	1	4	2	4	1
5	1	1	5	4	2	3
6	0	1	1	1	3	0

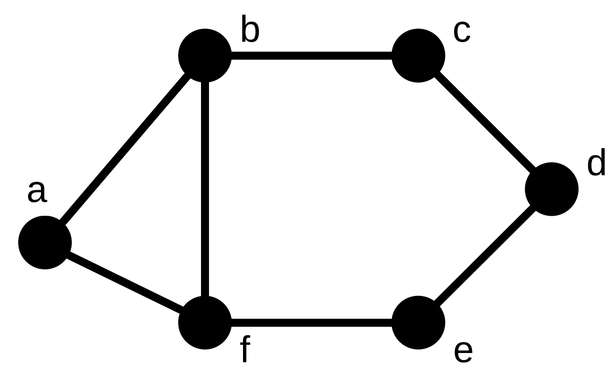
X^3

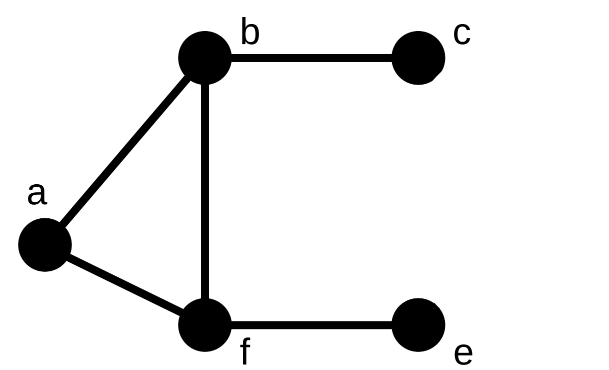
	1	2	3	4	5	6
1	2	0	4	1	1	1
2	0	6	2	5	6	1
3	4	2	13	7	7	5
4	1	5	7	8	7	4
5	1	6	7	7	12	2
6	1	1	5	4	2	3

X^4

Subgraphs

- Set of nodes
  - Is just a set of nodes
- A subgraph
  - Is set of nodes together with ties among them
- An induced subgraph
  - Subgraph defined by a set of nodes
  - Like pulling the nodes and ties out of the original graph





Subgraph induced by considering the set {a,b,c,f,e}

Components

- Maximal sets of nodes in which every node can reach every other by some path (no matter how long)
- A graph is *connected* if it has just one component

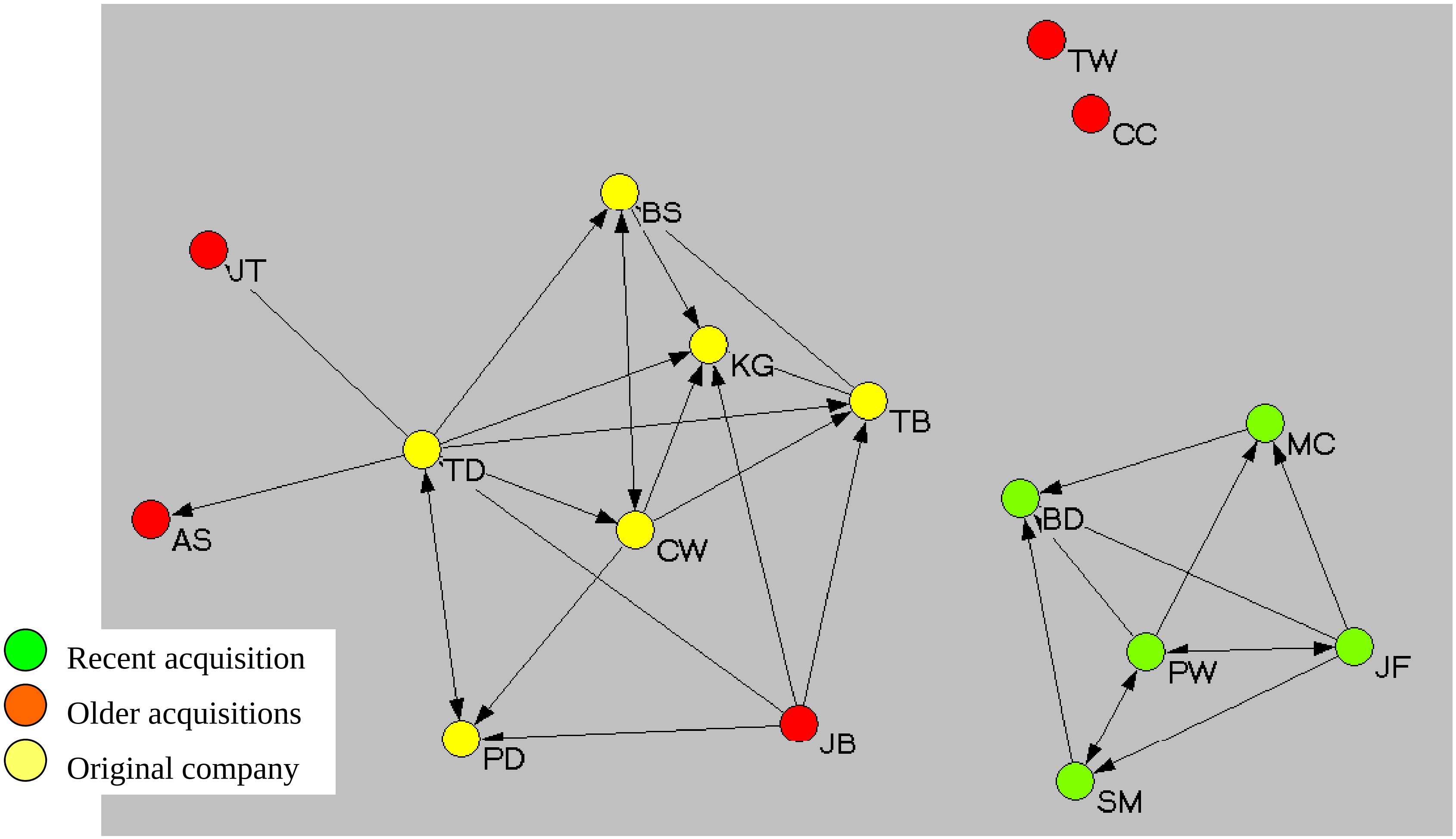
It is relations (types of tie) that define different networks, not components. A network that has two components remains one (disconnected) network.

Components in Directed Graphs

- Strong component
  - There is a directed path from each member of the component to every other
- Weak component
  - There is an undirected path (a weak path) from every member of the component to every other
  - Is like ignoring the direction of ties – driving the wrong way if you have to

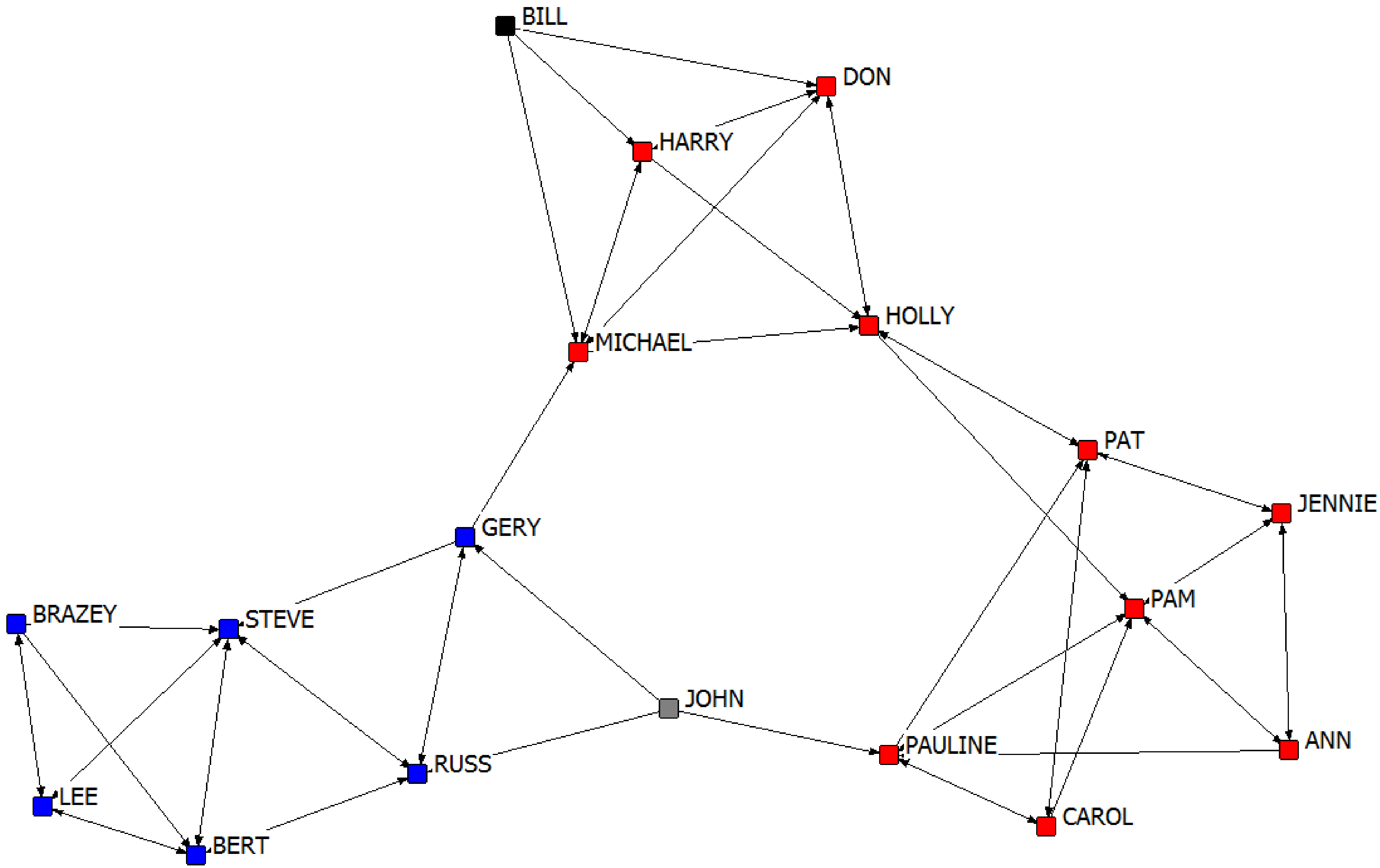
A network with 4 weak components

Who you go to so that you can say 'I ran it by ____, and she says ...'



Data drawn from Cross, Borgatti & Parker 2001.

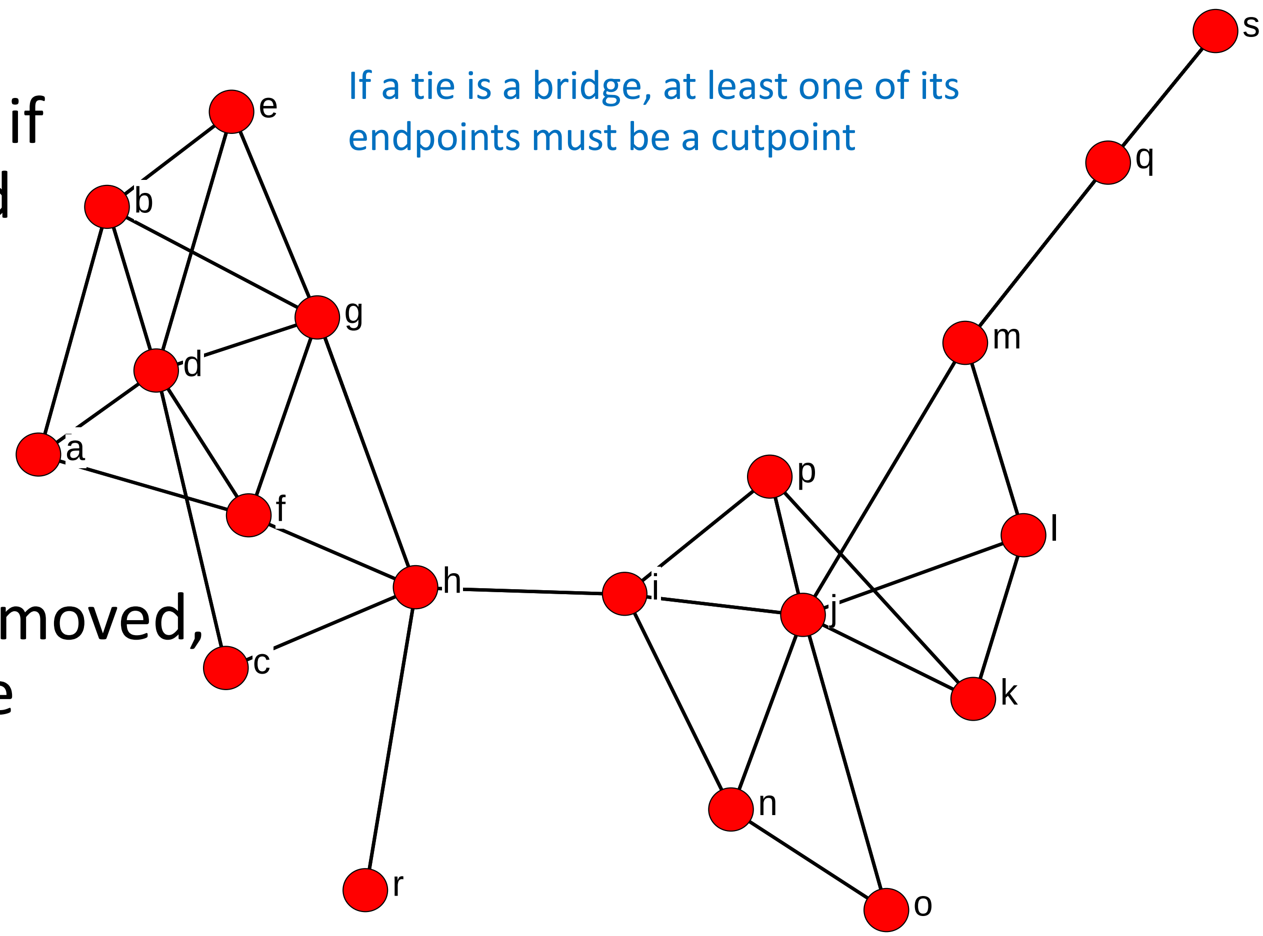
Strong components



Cutpoints and Bridges

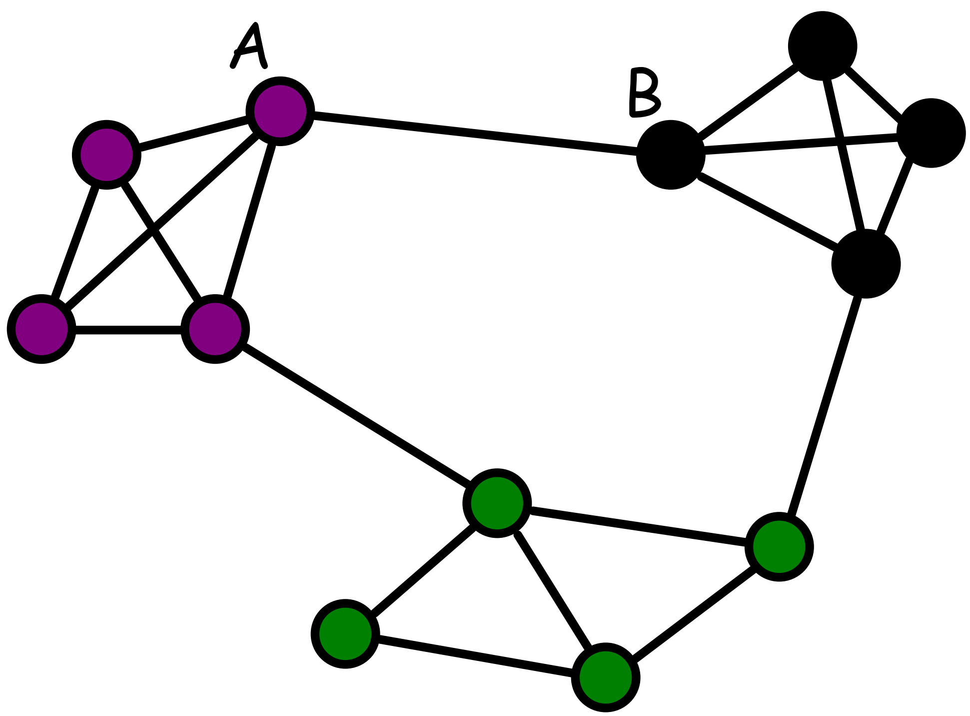
- Cutpoint
  - A node which, if deleted, would increase the number of components
- Bridge
  - A tie that, if removed, would increase the number of components

If a tie is a bridge, at least one of its endpoints must be a cutpoint



Local Bridge of Degree K

- A tie that connects nodes that would otherwise be at least *k* steps apart

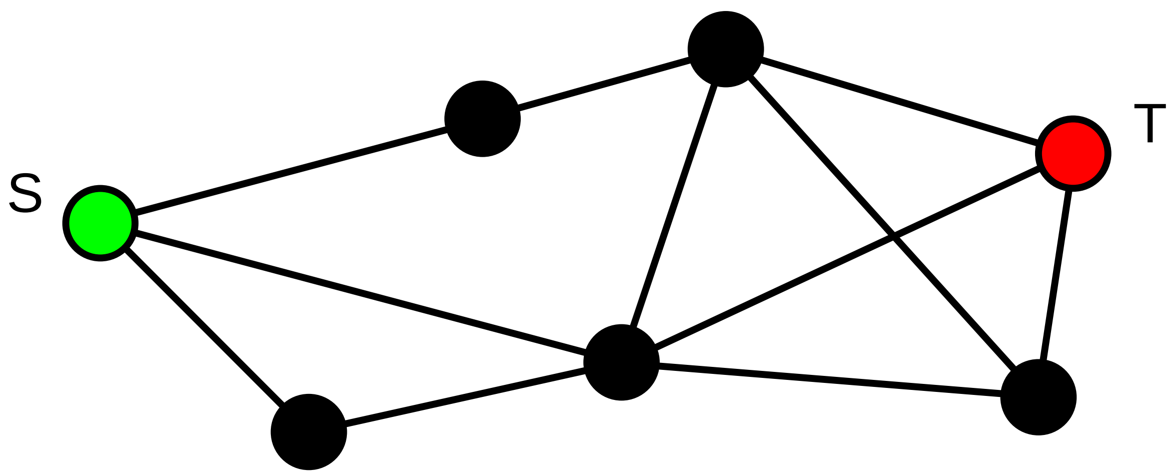


Cutsets

- Vertex cut sets (aka cutsets)
  - A set of vertices S = {u,v,…} of minimal size whose removal would increase the number of components in the graph
- Edge cut sets
  - A set of edges S = {(u,v),(s,t)…} of minimal size whose removal would increase the number of components in the graph

Independent Paths

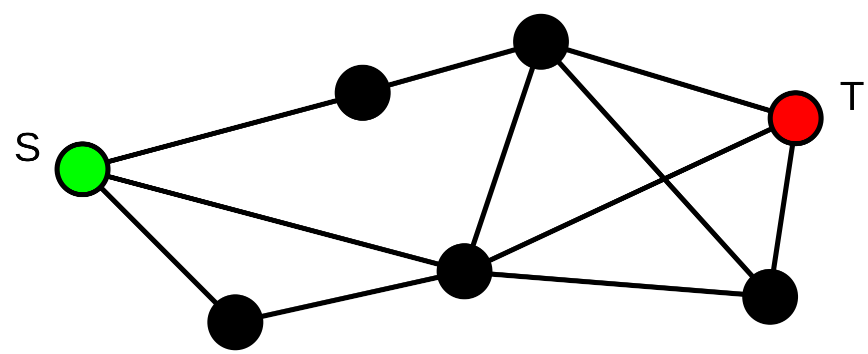
- A set of paths is node-independent if they share no nodes (except beginning and end)
  - They are line-independent if they share no lines



- 2 node-independent paths from S to T
- 3 line-independent paths from S to T

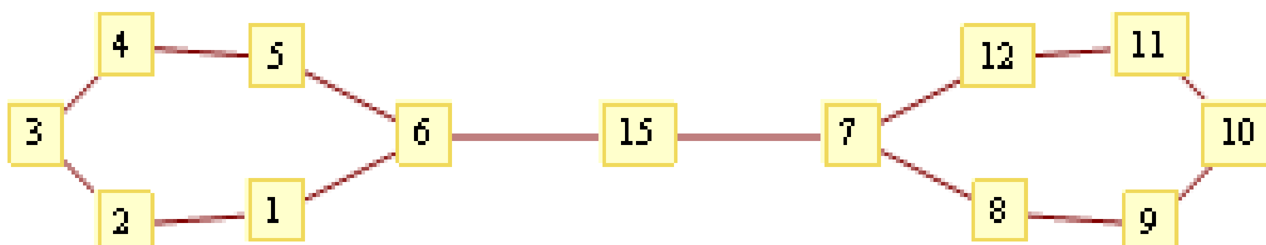
Connectivity

- Node connectivity κ(s,t) is minimum number of nodes that must be removed to disconnect s from t
- Line connectivity λ(s,t) is the minimum number of lines that must be removed to disconnect s from t



Bi-Components (Blocks)

- A bicomponent is a maximal subgraph such that every node can reach every other by at least two node-independent paths
- Bicomponents contain no cutpoints



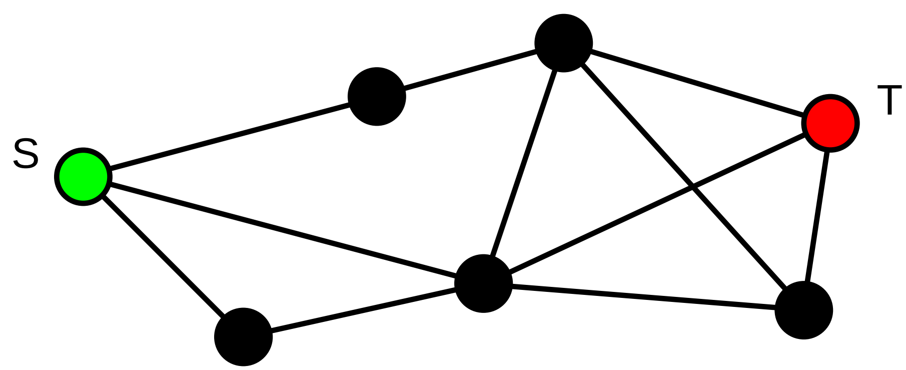
There are four bicomponents in this graph:
{1 2 3 4 5 6}, {6 15}, {15 7}, and {7 8 9 10 11 12}

Menger's Theorem

- Menger proved that the number of line independent paths between s and t equals the line connectivity $\lambda(s,t)$
- And the number of node-independent paths between s and t equals the node connectivity $\kappa(u,v)$

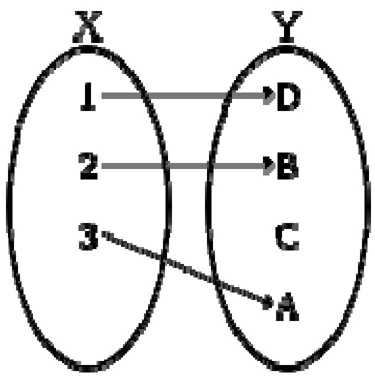
Maximum Flow

- If ties are pipes with capacity of 1 unit of flow, what is the maximum # of units that can flow from s to t?
- Ford & Fulkerson show this was equal to the number of line-independent paths

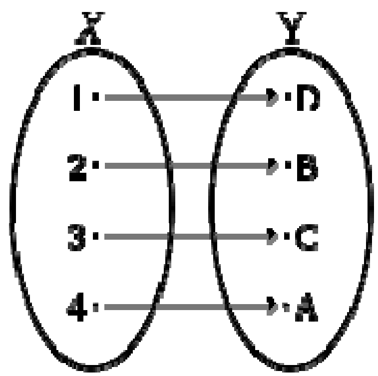


THE END

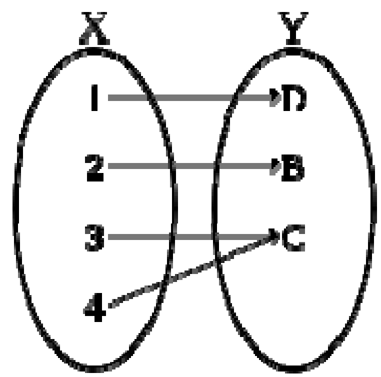
Special Types of Relations



Injective (1 to 1)
Every "tie" goes to
a different other



Bijective
1 to 1 correspondence



Surjective (onto)