# DATA PREPARATION

Dr. Aric LaBarr

Institute for Advanced Analytics

# Course Layout

**Data Preparation**
- Transactional Data
- Recency vs. Frequency
- Network Features

**Anomaly Models**
- Univariate Analysis
- Clustering
- Isolation Forests
- CADE

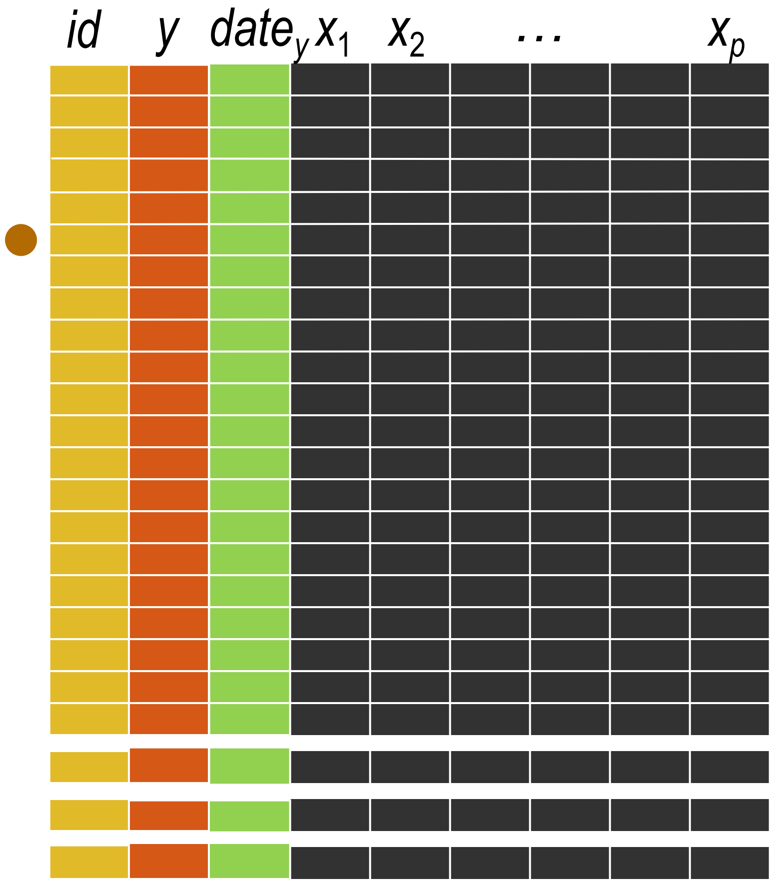
**Fraud Supervised Models**
- SMOTE
- Models
- Labeled vs. Unlabeled Bias
- Not Fraud Model
- Evaluation

**Clusters of Not Goods**
- Cluster Analysis
- Social Network Analysis

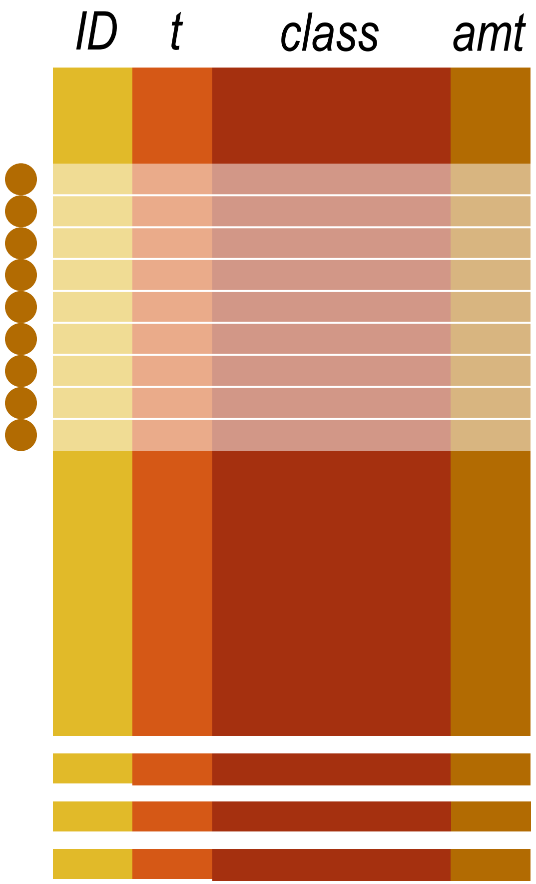
**Implement**
- Investigators
- Traffic Light Indicators
- Backtesting

# FEATURE ENGINEERING

# Transaction Data




Model Development Data




Transaction Data

# Transaction Data Examples

- There are many different fields where transactional data plays an important role:
  - Credit card purchasing data
  - Medical claims data
  - Insurance claims data
  - Retail purchasing data
  - Etc.

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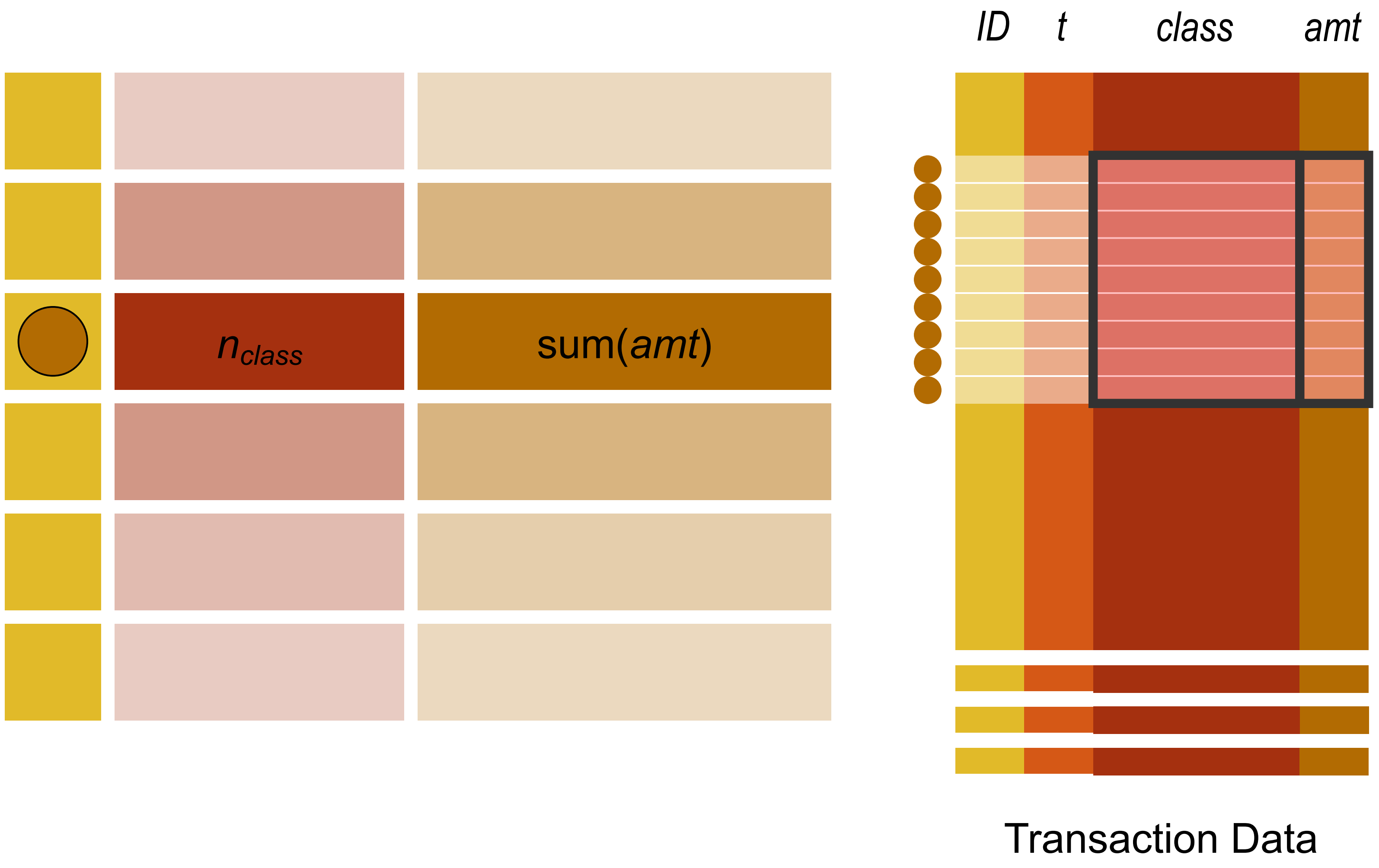
THINK OF YOUR DATA SPECIFICALLY!

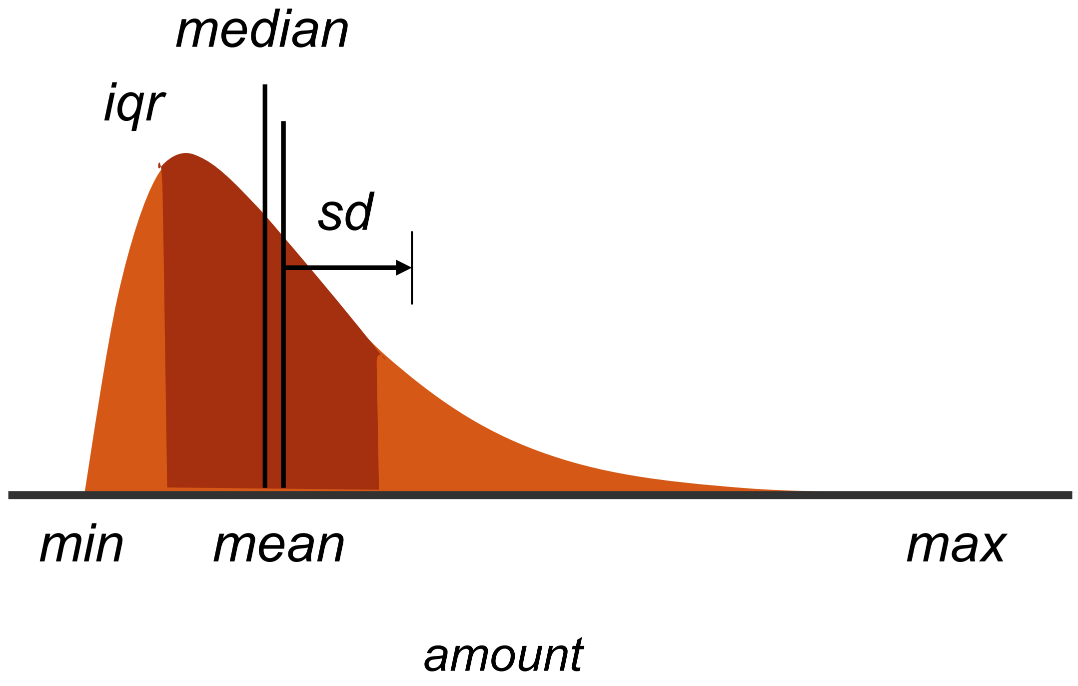
# Transactions Data

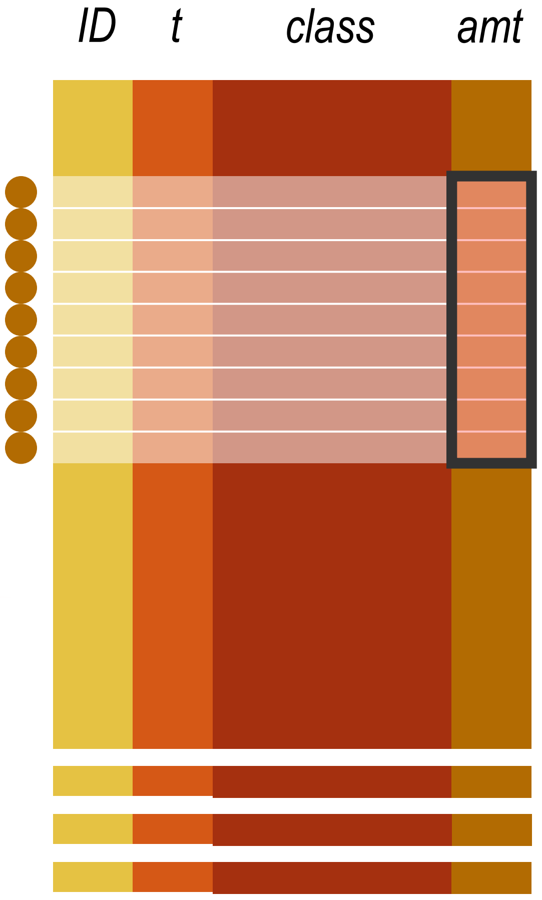
- Advantages
  - Highly Detailed
  - Captures Individual Behavior
  - Strong Target Correlation Possible
- Challenges
  - Highly Detailed
  - Difficult to Obtain
  - Difficult to Process

# Input Possibilities: Tabulations



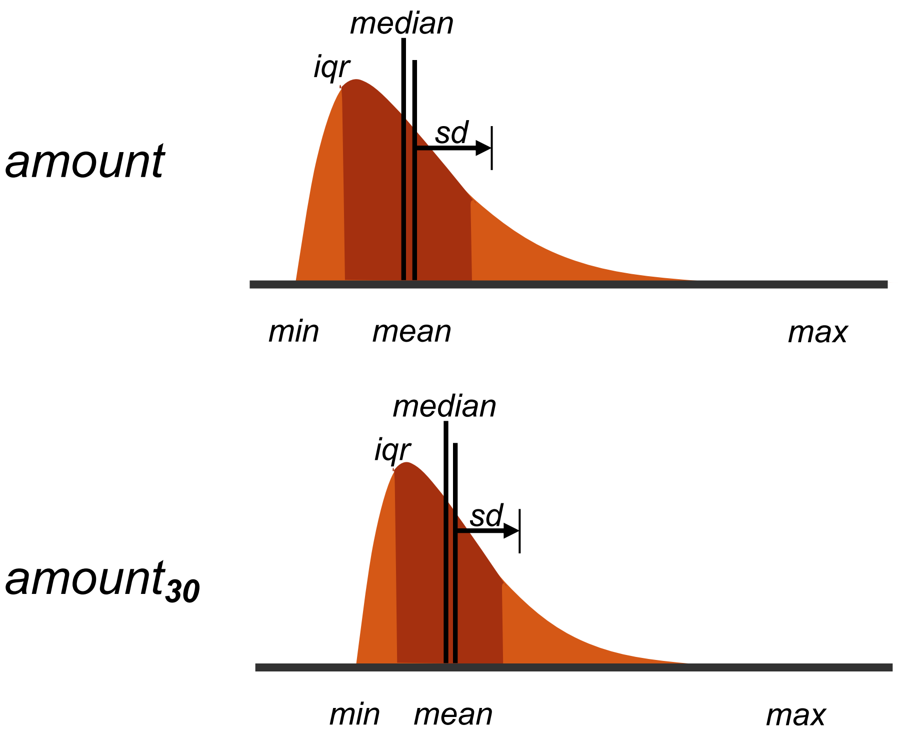
# Input Possibilities: Distributions

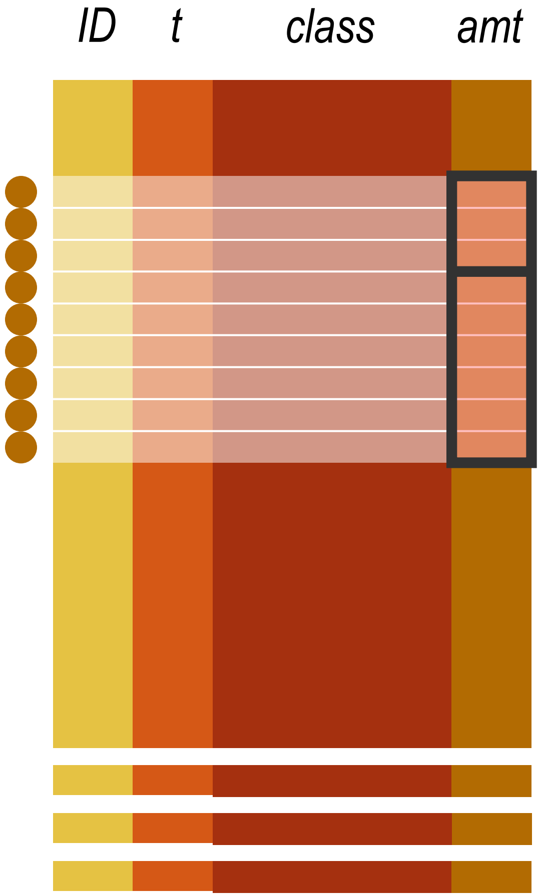



Transaction Data

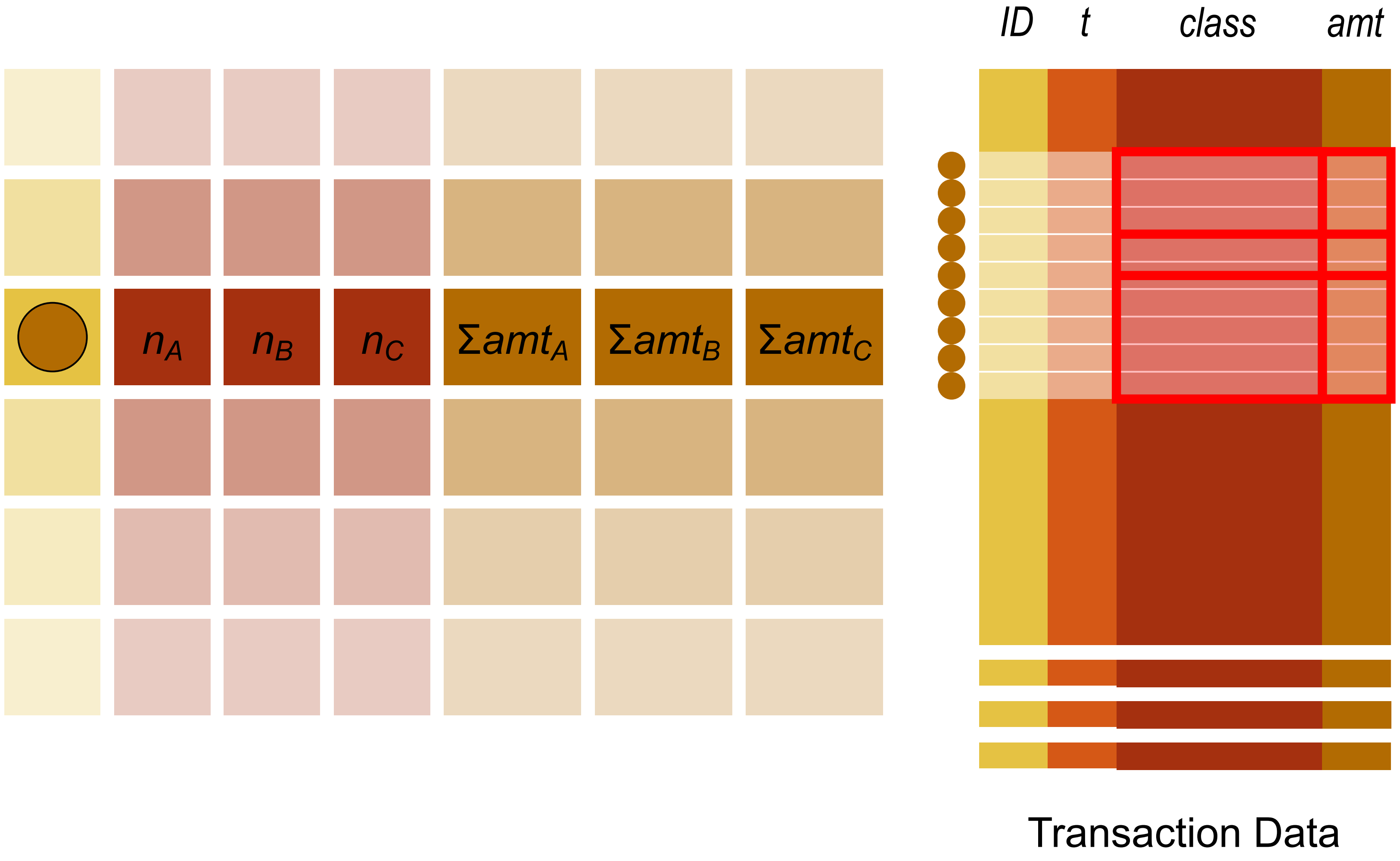
# Input Possibilities: Stratifications



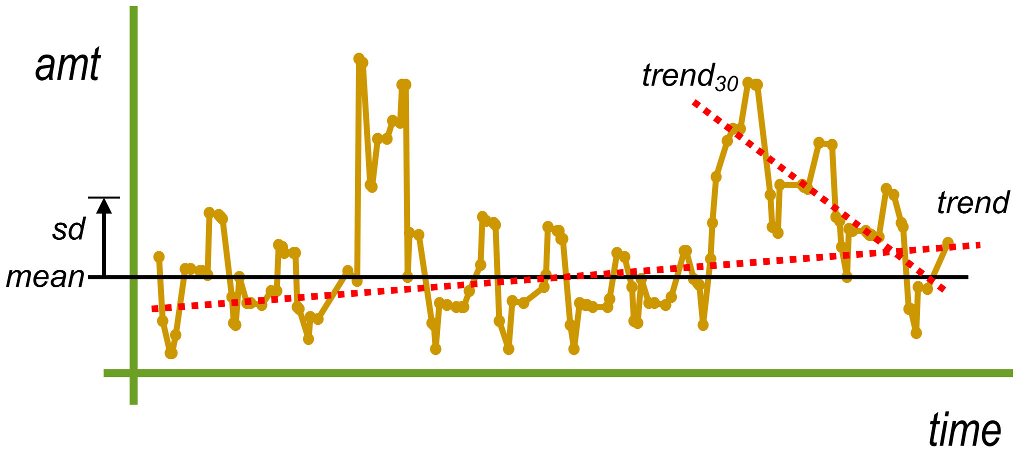



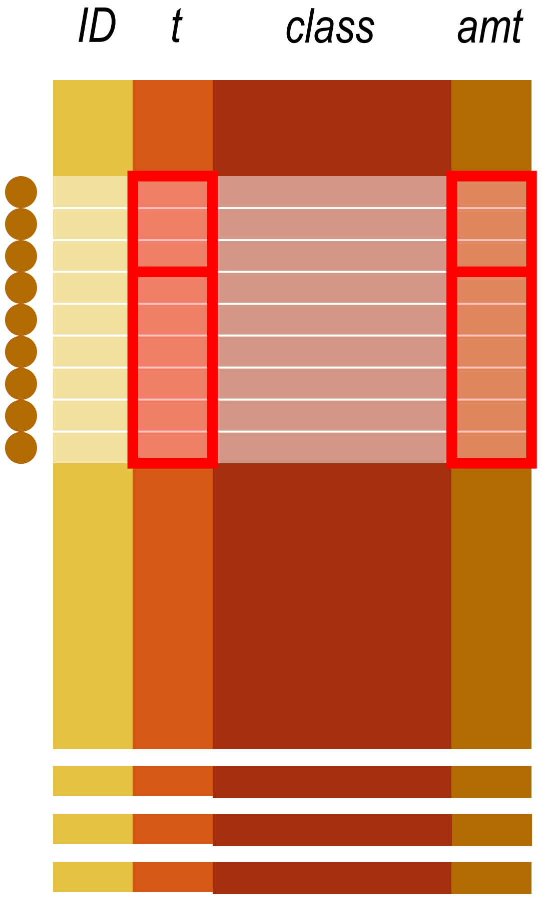

Transaction Data

# Input Possibilities: Profiles



# Input Possibilities: Time Series




Transaction Data

# Process Transactions

- Here are the steps you need to take to process transactional data:
  1. Select your data.
  2. Sort your data.
  3. Augment your data.
  4. Process by ID.
  5. Finalize.

# Grouping Transaction-Derived Inputs

- Examples
  - Mean of last five transactions
  - Standard deviation of transactions in last 14 days
  - Largest transaction per week
  - Slope of line fit to number of transactions per week (negative?)

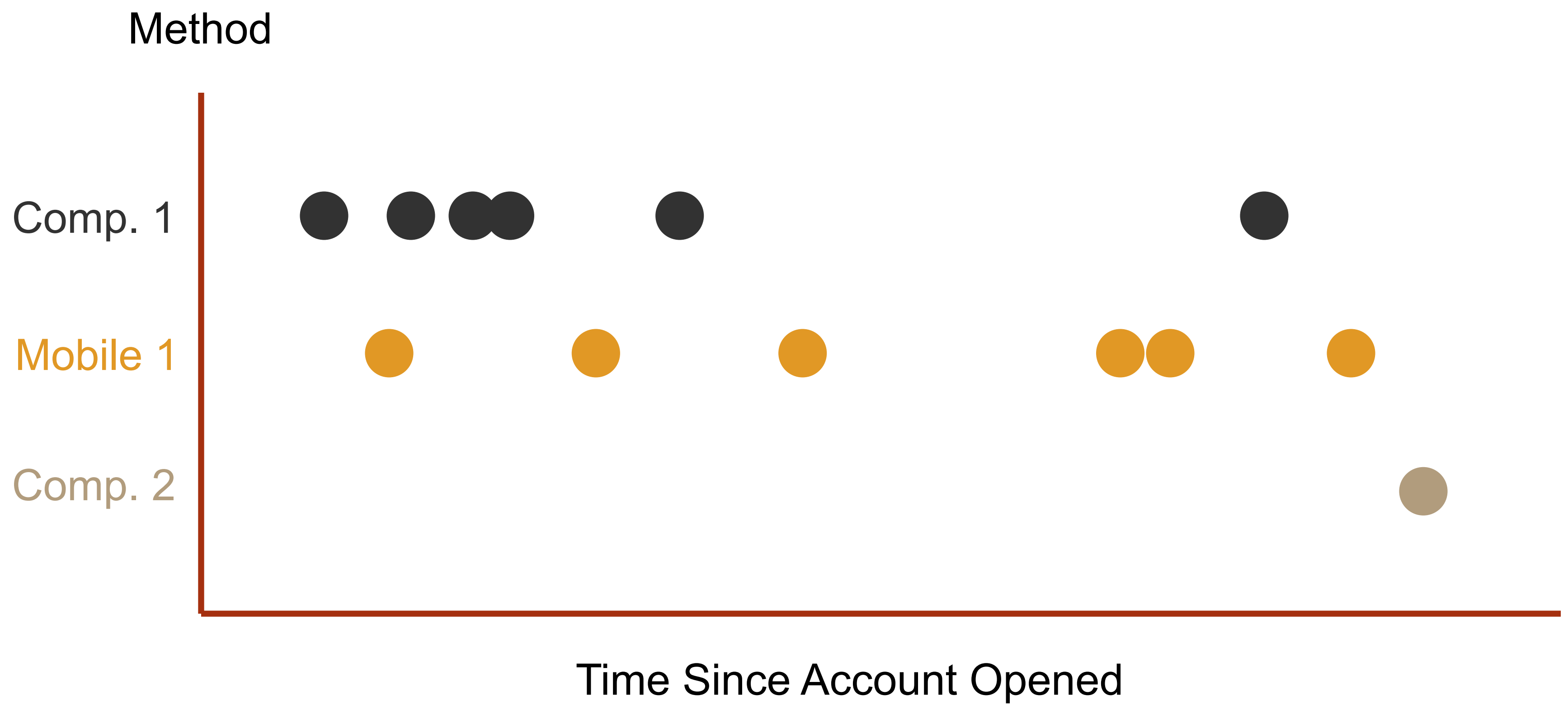
# RECENCY & FREQUENCY

# Recency & Frequency

- Transactional data provides extensive information.
- Two of the most important things in fraud detection (as well as other fields) are **recency** and **frequency** of transaction.

- **Recency** – time in between transactions
- **Frequency** – how often transactions occur

# Online Account Access Example

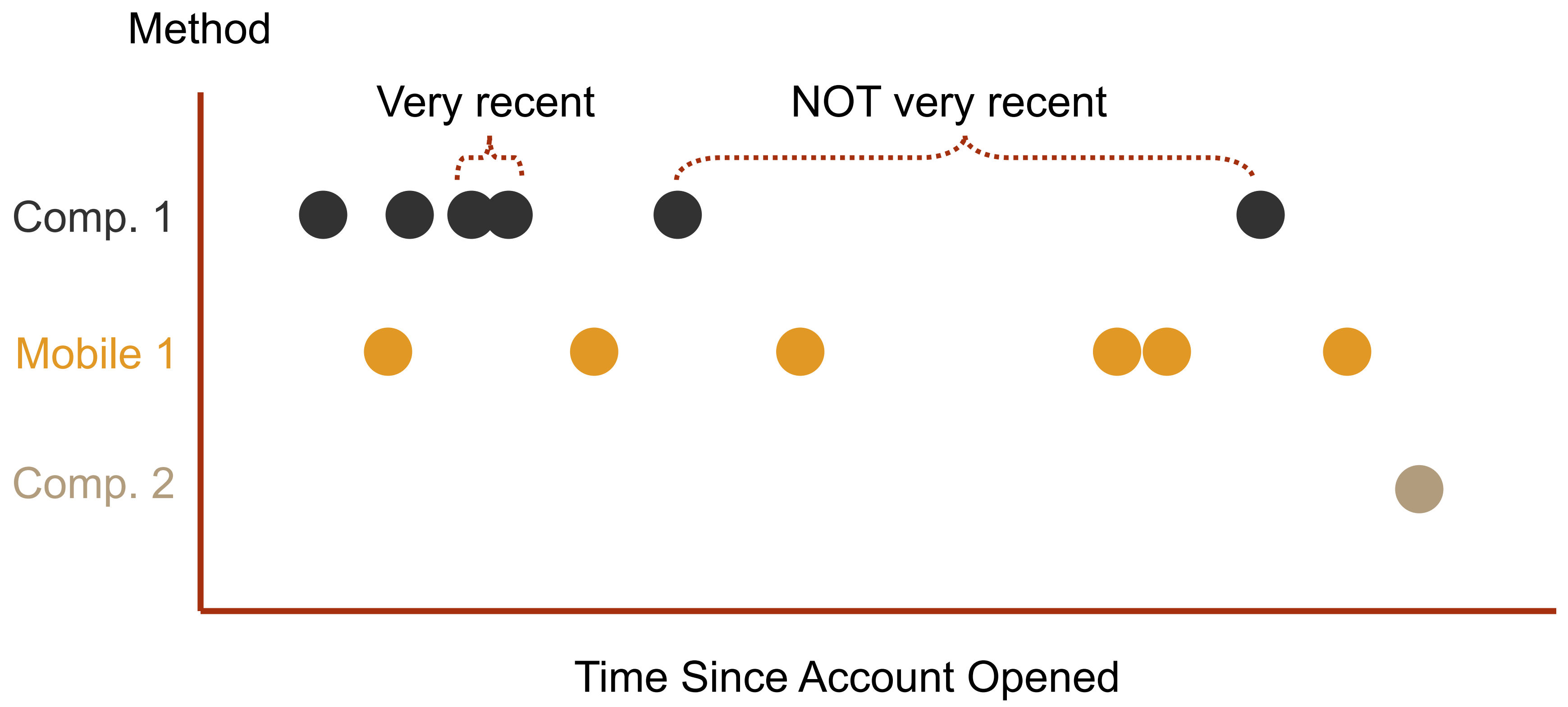


# Recency

- **Recency** – time in between transactions

- Easy features:
  - Time in between transactions
  - Time since last transaction

# Online Account Access Example



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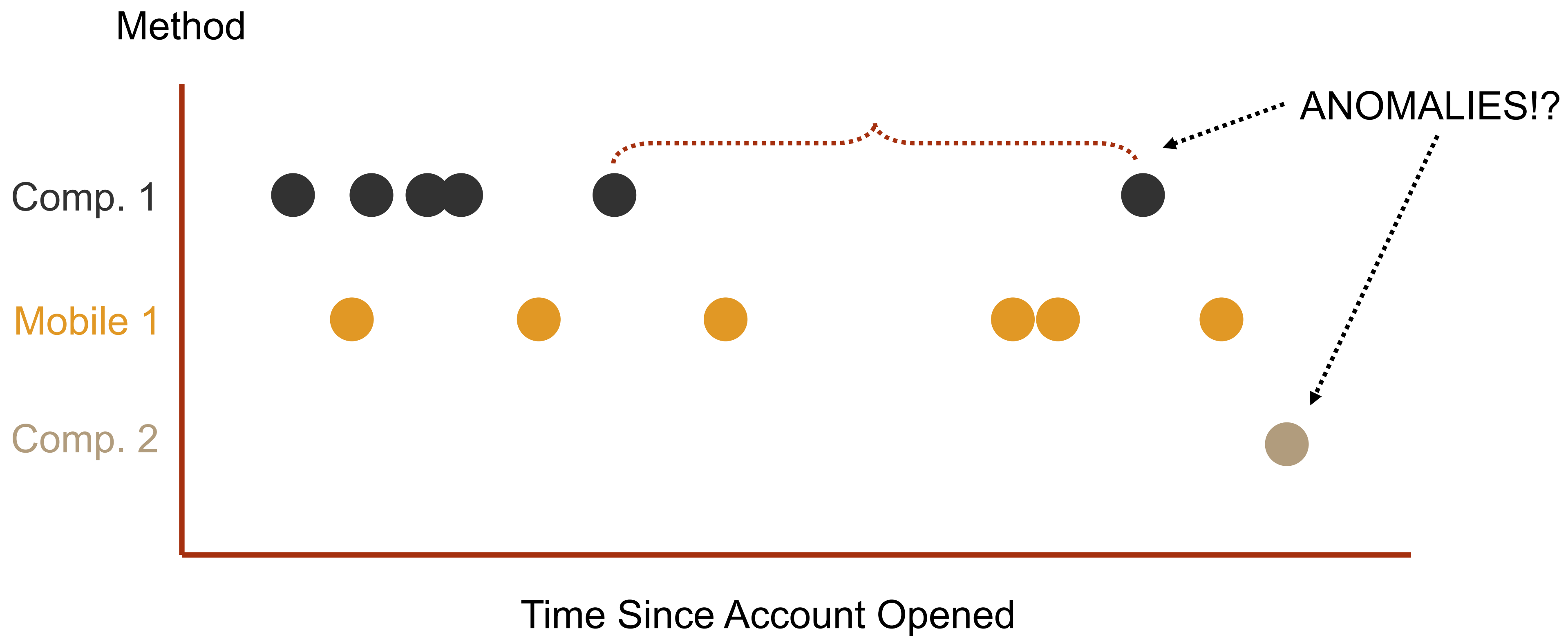
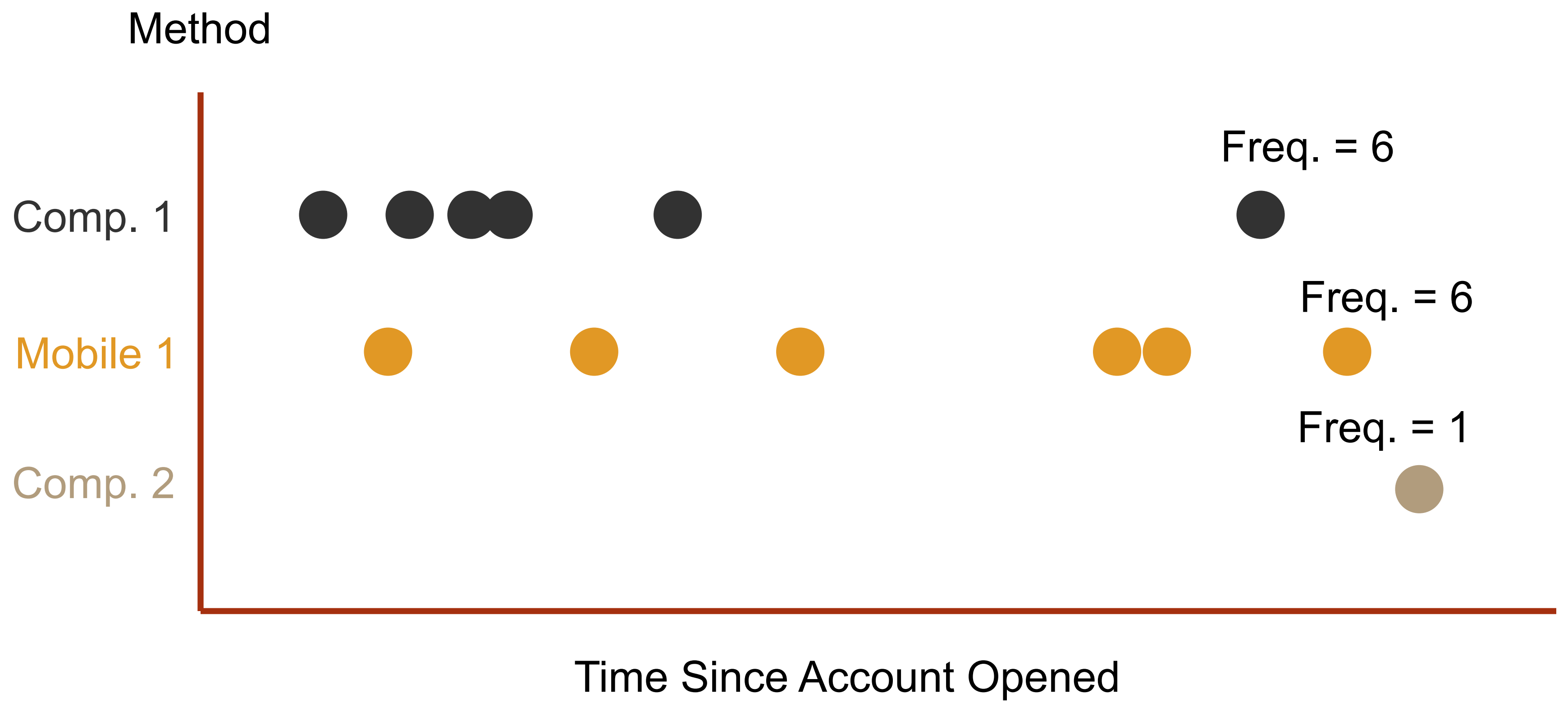


# Frequency

- **Frequency** – how often transactions occur

- Easy features:
  - How many transactions total
  - How many transactions per group
  - Ratio of frequency by group to days active

# Online Account Access Example



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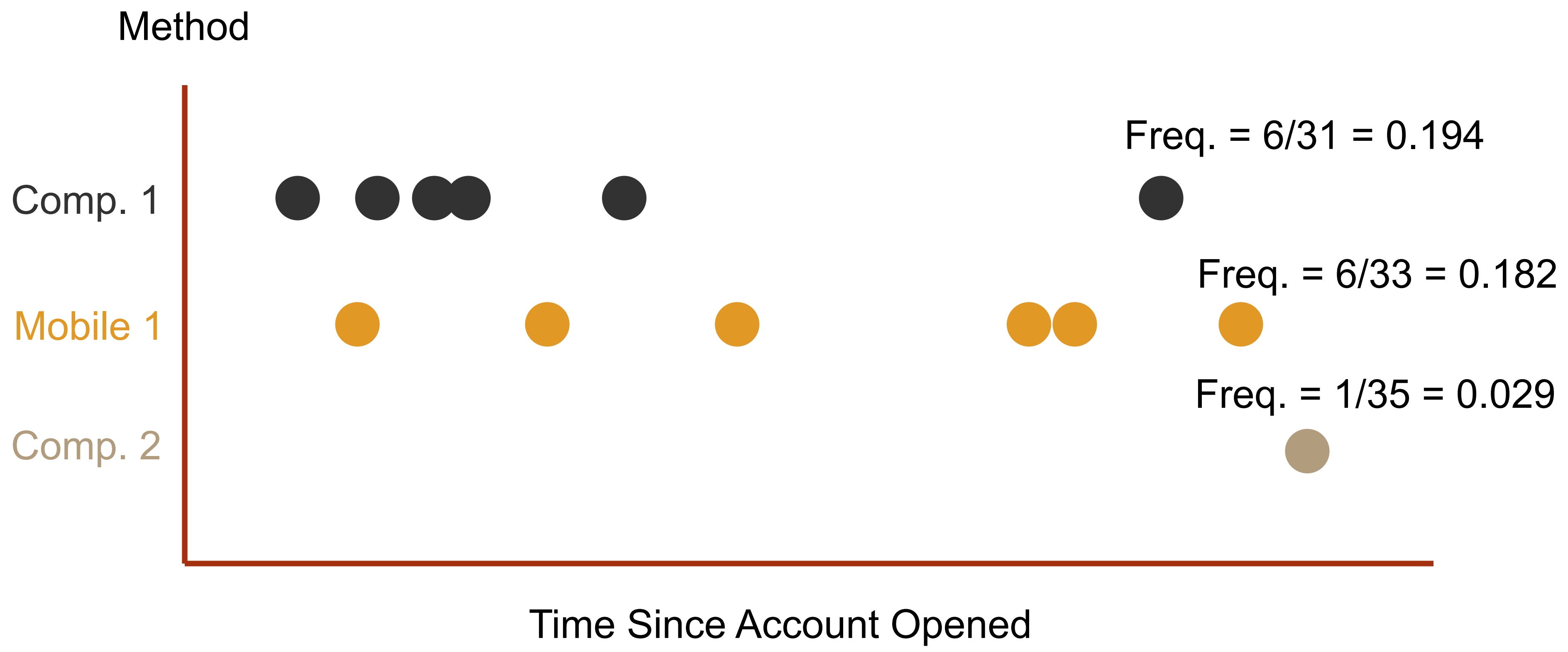


# TRANSFORMING CATEGORIES

# Categorical Data

| Examples | Cardinality |
|---|---|
| Physical characteristics | 1 |
| ⋮ | 10 |
| Education level | |
| ⋮ | |
| State | |
| ⋮ | 100 |
| Postal code | 1000 |
| Address | 1000000 |
| Social security number | 100000000 |
| Free-form text | *infinite* |

# Categorical Data

Physical characteristics

⋮

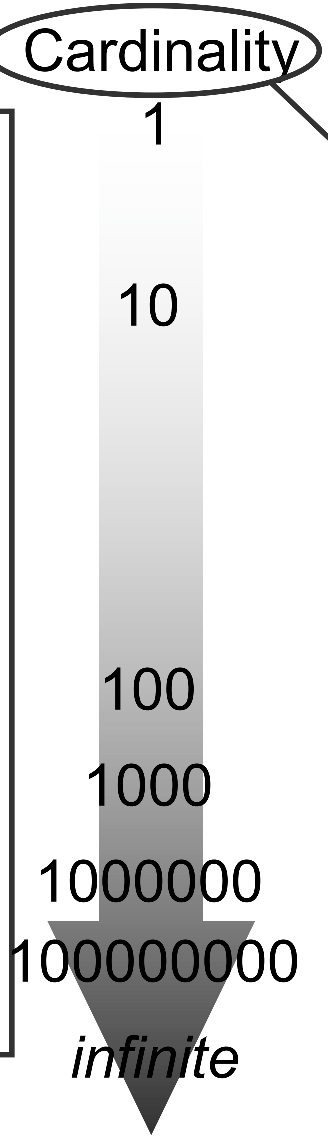
Education level

⋮

State

⋮

Postal code
Address
Social security number
Free-form text




Number of
elements
in a set.

# Strategies

| | Cardinality | Strategy |
|---|---|---|
| Physical characteristics | 1 | None / Model Based |
| ⋮ | 10 | |
| Education level | | Recoding |
| ⋮ | | |
| State | | |
| ⋮ | 100 | Transformations |
| Postal code | 1000 | |
| Address | 1000000 | |
| Social security number | 100000000 | Linking |
| Free-form text | *infinite* | Text Mining |

# Dummy Coding

| *X* |
|---|
| D |
| B |
| C |
| C |
| A |
| A |
| D |
| C |
| A |
| ⋮ |

| $D_A$ | $D_B$ | $D_C$ | $D_D$ |
|---|---|---|---|
| 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 1 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 |
| 0 | 0 | 1 | 0 |
| 1 | 0 | 0 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ |

# Thresholding

| *Level* | $N_i$ |
|---|---|
| A | 1562 |
| B | 970 |
| C | 223 |
| D | 111 |
| E | 85 |
| F | 50 |
| G | 23 |
| H | 17 |
| I | 12 |
| J | 5 |

# Thresholding

| *Level* | $N_i$ |
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| A | 1562 |
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| G | 23 |
| H | 17 |
| I | 12 |
| J | 5 |

Recombine to single new level, OTHER.

# Target-Based Enumeration

| *Level* | $N_i$ | $\Sigma Y_i$ | $p_i$ |
|---|---|---|---|
| A | 1562 | 430 | 0.28 |
| B | 970 | 432 | 0.45 |
| C | 223 | 45 | 0.20 |
| D | 111 | 36 | 0.32 |
| E | 85 | 23 | 0.27 |
| F | 50 | 20 | 0.40 |
| G | 23 | 8 | 0.35 |
| H | 17 | 5 | 0.29 |
| I | 12 | 6 | 0.50 |
| J | 5 | 5 | 1.00 |

# Target-Based Enumeration

| *Level* | $N_i$ | $\Sigma Y_i$ | $p_i$ |
|---|---|---|---|
| J | 5 | 5 | 1.00 |
| I | 12 | 6 | 0.50 |
| B | 970 | 432 | 0.45 |
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# Target-Based Enumeration

| $X$ | $N_i$ | $\Sigma Y_i$ | $p_i$ |
|---|---|---|---|
| 1 | 5 | 5 | 1.00 |
| 2 | 12 | 6 | 0.50 |
| 3 | 970 | 432 | 0.45 |
| 4 | 50 | 20 | 0.40 |
| 5 | 23 | 8 | 0.35 |
| 6 | 111 | 36 | 0.32 |
| 7 | 17 | 5 | 0.29 |
| 8 | 1562 | 430 | 0.28 |
| 9 | 85 | 23 | 0.27 |
| 10 | 223 | 45 | 0.20 |

New Ordinal Input

# Weight of Evidence

| Level | $N_i$ | $\Sigma Y_i$ | $p_i$ | $\log(p_i/1-p_i)$ |
|---|---|---|---|---|
| J | 5 | 5 | 1.00 | . |
| I | 12 | 6 | 0.50 | 0.00 |
| B | 970 | 432 | 0.45 | -0.10 |
| F | 50 | 20 | 0.40 | -0.18 |
| G | 23 | 8 | 0.35 | -0.27 |
| D | 111 | 36 | 0.32 | -0.32 |
| H | 17 | 5 | 0.29 | -0.38 |
| A | 1562 | 430 | 0.28 | -0.42 |
| E | 85 | 23 | 0.27 | -0.43 |
| C | 223 | 45 | 0.20 | -0.60 |

Old Categorical Input

New Numeric Input

# Level Clustering

| *Level* | $N_i$ | $\Sigma Y_i$ | $p_i$ | $\log(p_i/1-p_i)$ |
|---|---|---|---|---|
| J | 5 | 5 | 1.00 | . |
| I | 12 | 6 | 0.50 | 0.00 |
| B | 970 | 432 | 0.45 | -0.10 |
| F | 50 | 20 | 0.40 | -0.18 |
| G | 23 | 8 | 0.35 | -0.27 |
| D | 111 | 36 | 0.32 | -0.32 |
| H | 17 | 5 | 0.29 | -0.38 |
| A | 1562 | 430 | 0.28 | -0.42 |
| E | 85 | 23 | 0.27 | -0.43 |
| C | 223 | 45 | 0.20 | -0.60 |

# Level Clustering

| *Level* | $N_i$ | $\Sigma Y_i$ | $p_i$ | $\log(p_i/1-p_i)$ |
|---|---|---|---|---|
| CL1 | 1037 | 463 | 0.45 | -0.09 |
| CL2 | 134 | 44 | 0.33 | -0.31 |
| CL3 | 1664 | 458 | 0.28 | -0.42 |
| CL4 | 223 | 45 | 0.20 | -0.60 |

New Categorical Input ***or*** New Numeric Input

# Geocoding

| ZIP | Longitude | Latitude |
| --- | --- | --- |
| 02713 | -70.8017 | 41.45222 |
| 02840 | -71.3114 | 41.49438 |
| 04848 | -68.9096 | 44.30417 |
| 08739 | -74.0549 | 40.02756 |
| 10927 | -73.9604 | 41.19228 |
| 10960 | -73.9187 | 41.08947 |
| 13640 | -75.9098 | 44.33451 |
| 14555 | -76.9867 | 43.27016 |
| 19939 | -75.2052 | 38.57527 |
| 19944 | -75.0509 | 38.46811 |
| 20004 | -77.0275 | 38.89254 |

Transform zip code to location.

# Derived Fields Specific to Insurance

- Approximate the distance from the claimant's address to the adjuster's location using only zip codes.

Zipcode ⇨ (Latitude,Longitude)

[(Lat_1,Long_1),(Lat_2,Long_2)] ⇨ Distance

⇨

(Claimant Zipcode, Adjuster Zipcode) ⇨ Distance

# Derived Fields from Text

- Text mining can provide an immense amount of data when limited data may seem to exist.
- Mining the text data may reveal patterns that can be adapted into input variables.

# NETWORK FEATURES

# Occupational View

- "Everything is a nail to a kid with a hammer."

- The view of the world around us is influenced by our experiences:
  - Economist: World is a supply/demand curve.
  - Chemist: World is a set of chemical equations.
  - Statistician: World is a collection of observations with dependent and independent variables.

# Society – Statisticians

- Statisticians typically view society as a collection of individuals who have distinct, measureable characteristics.

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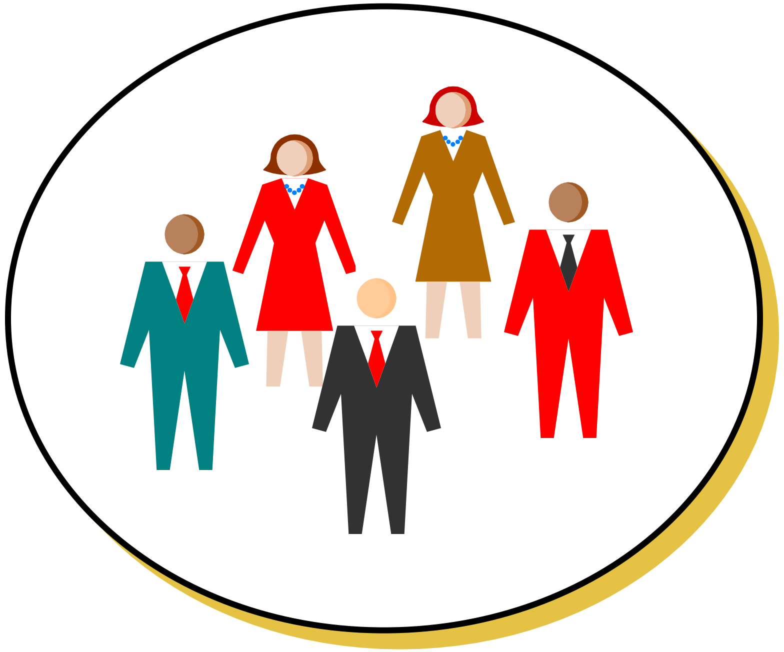

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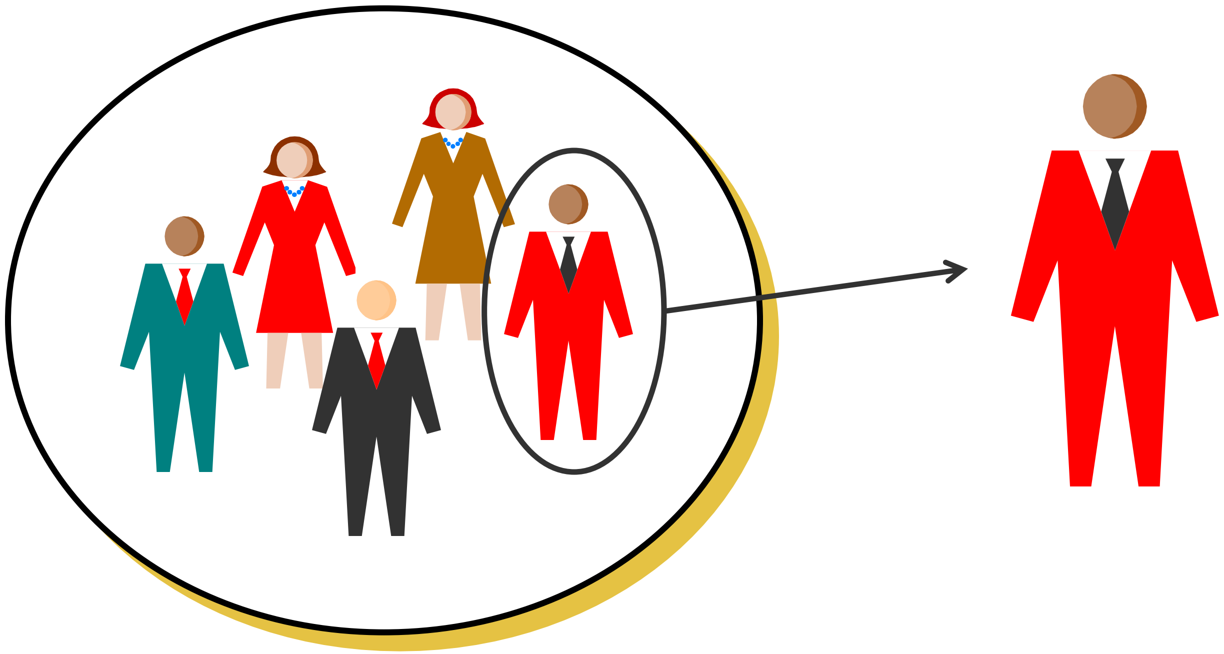

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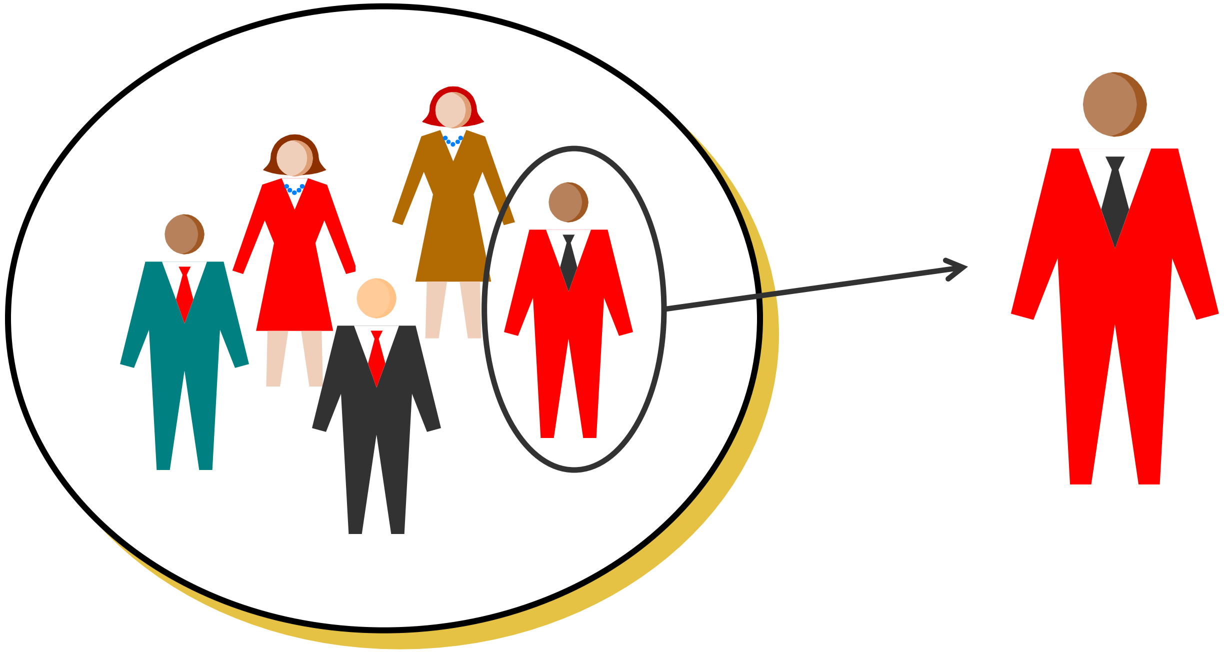

Characteristics:
- Age
- Weight
- Income
- Education
- Etc.

# Statisticians' Data Structure

- Data structure is typically rectangular in nature.

| Name | Age | Weight | Income | Years of College Education |
|---|---|---|---|---|
| Bill | 54 | 190 | $48,000 | 4 |
| Tina | 26 | 135 | $95,000 | 4 |
| Larry | 39 | 215 | $101,000 | 9 |
| … | … | … | … | … |

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Comparing Individuals

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Comparing Variables

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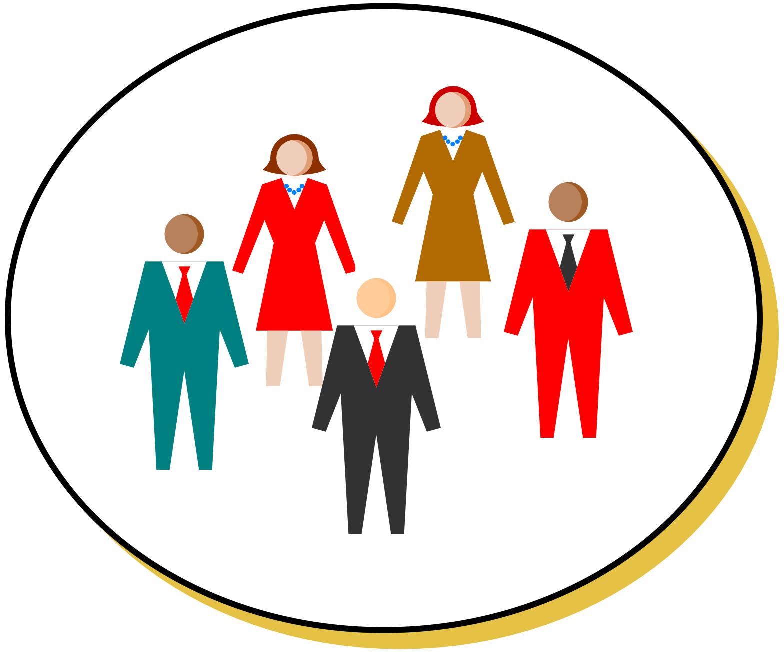
# Society – Sociometrists

- J L Moreno founded a social science called **sociometry**, where **sociometrists** believe that society is made up of individuals **and** their social, economic, or cultural ties.



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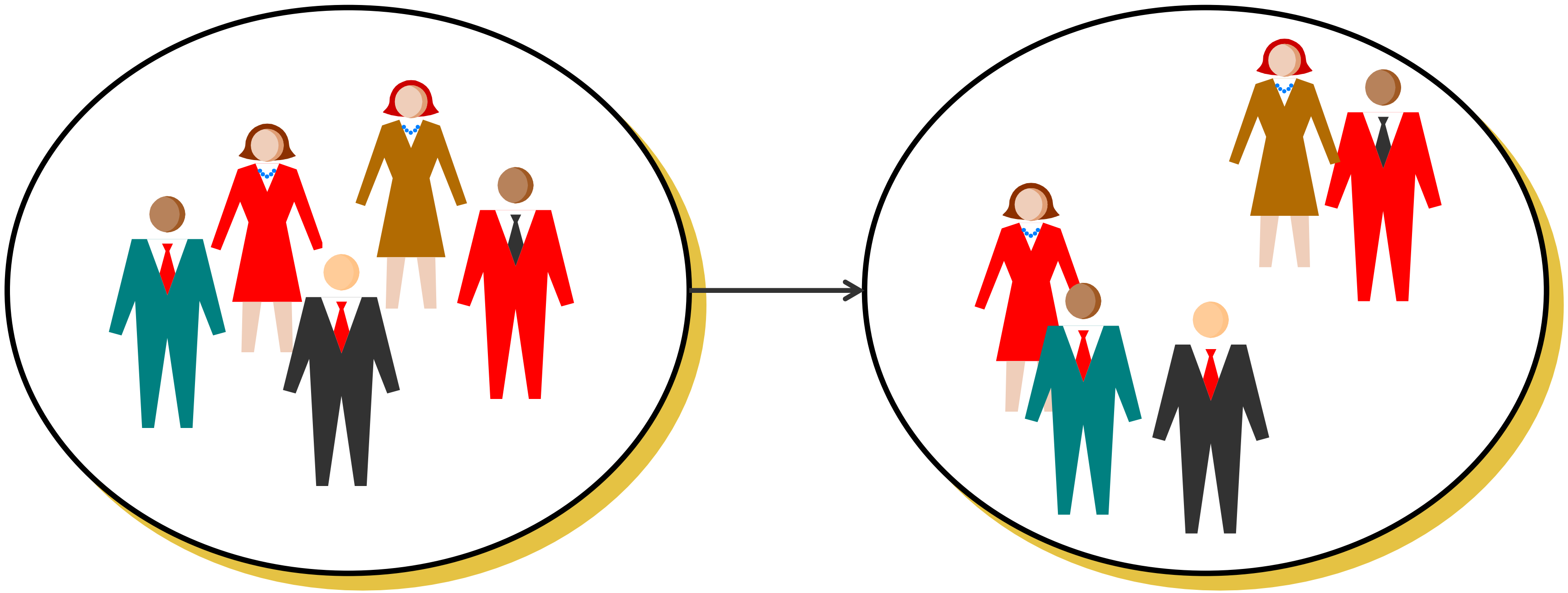

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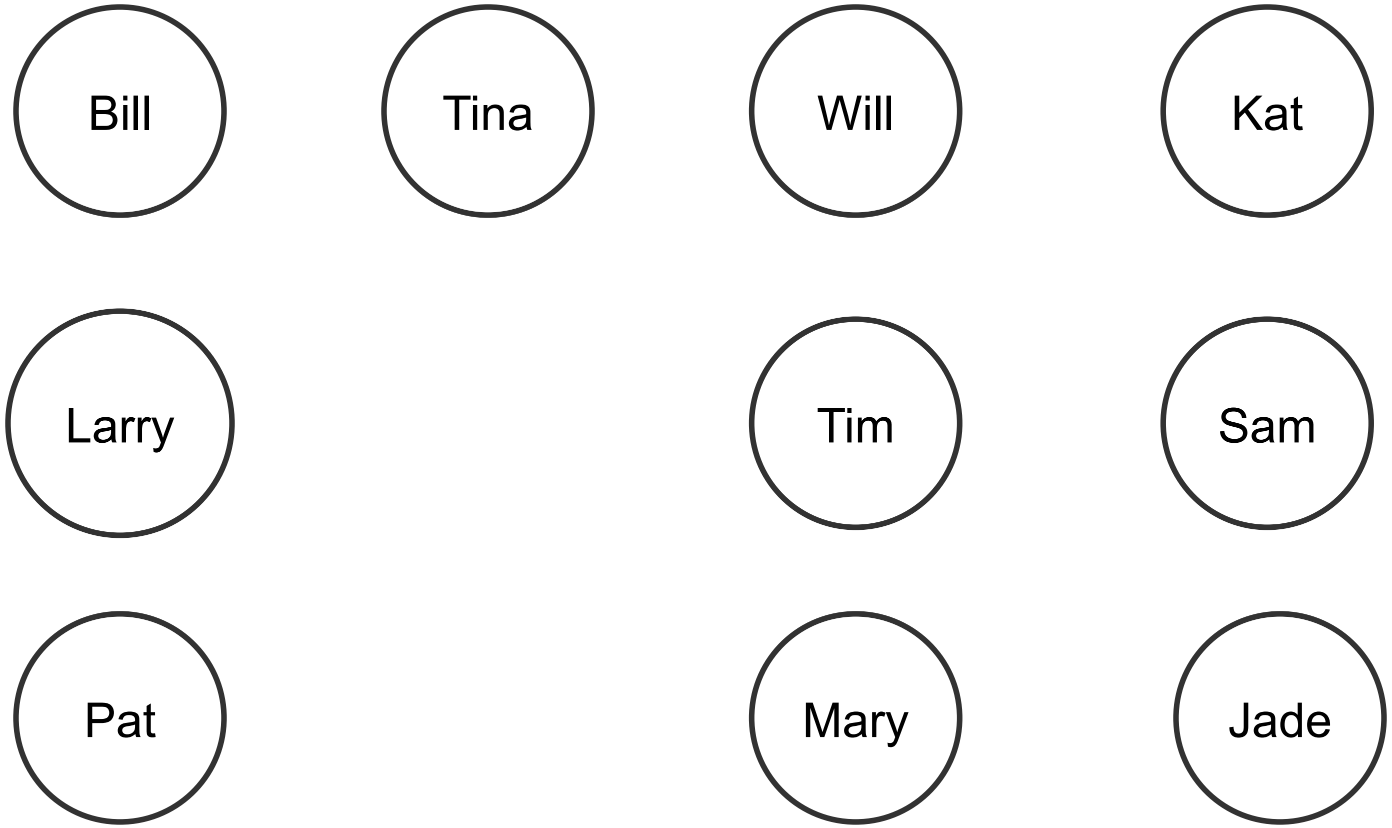
- The importance is not only on the individual’s characteristics, but also on the patterns of an individual’s interactions with other individuals.
- The interactions themselves are just as important as who the individual connects to.

# Exploring Social Networks

- Sociometrists use **graph networks (link graphs)** to visualize social networks.
- These graph networks reveal a structure to the data that can not be seen by basic summary statistics.
- Each of the circles are referred to as **nodes**.

# Exploring Social Networks



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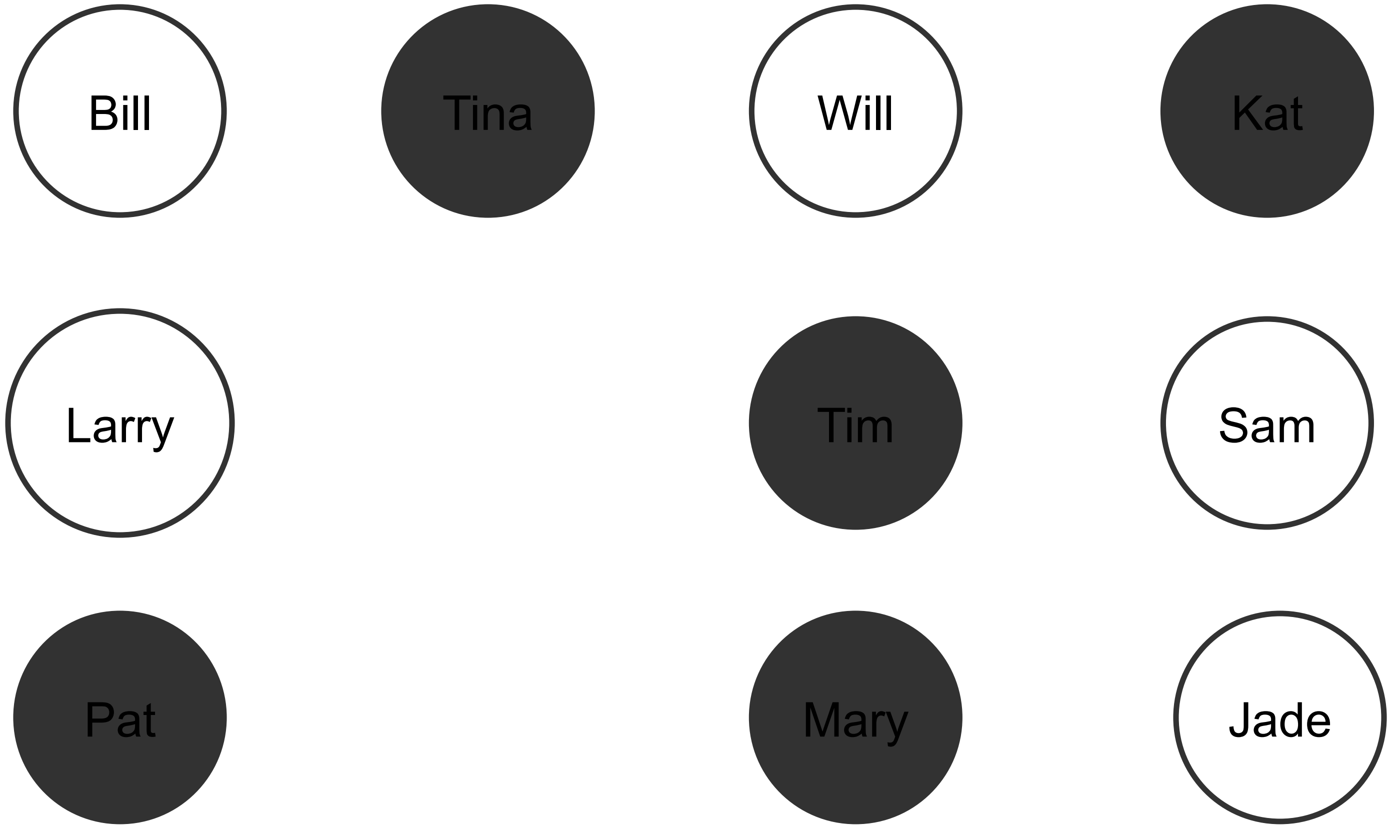

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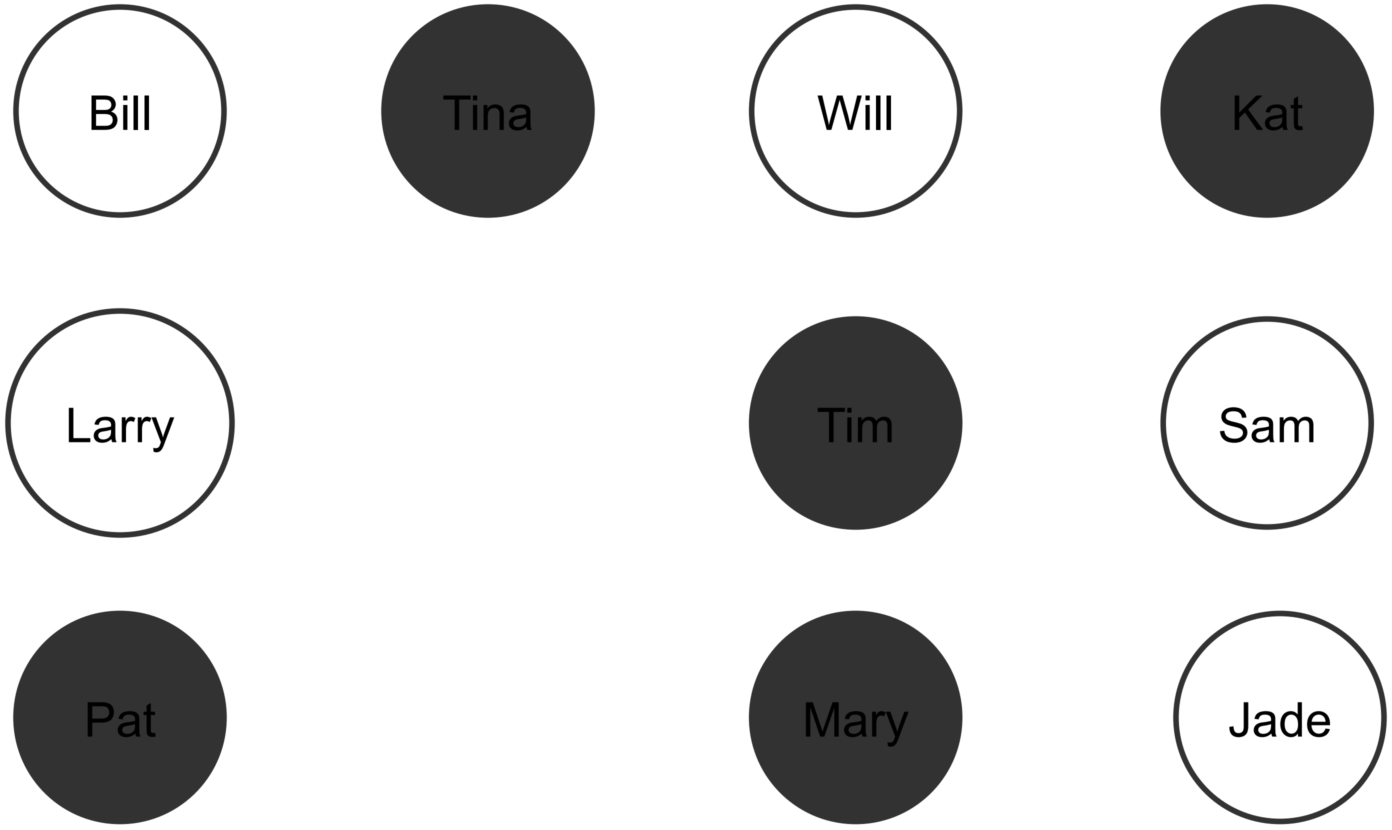

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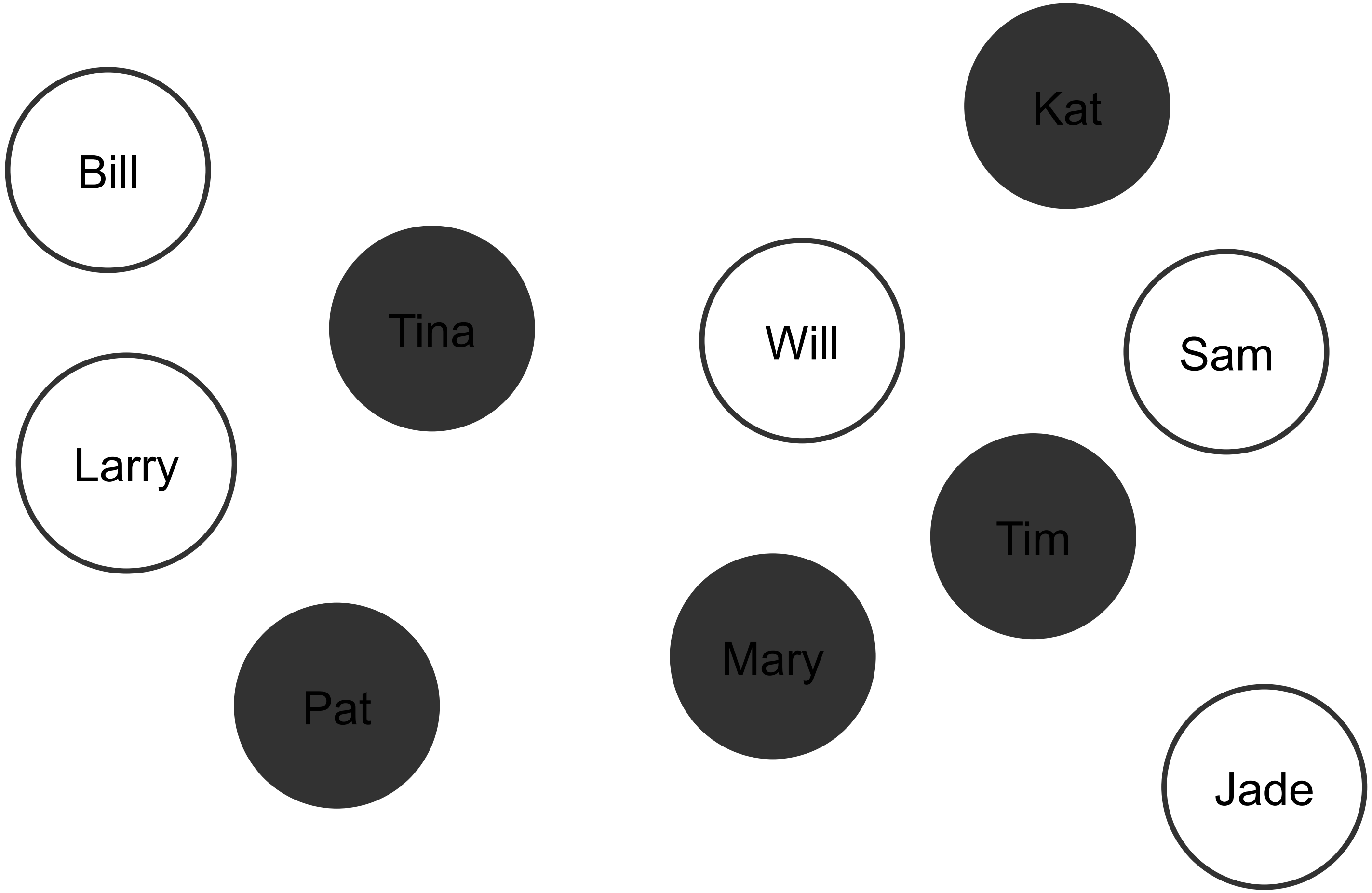

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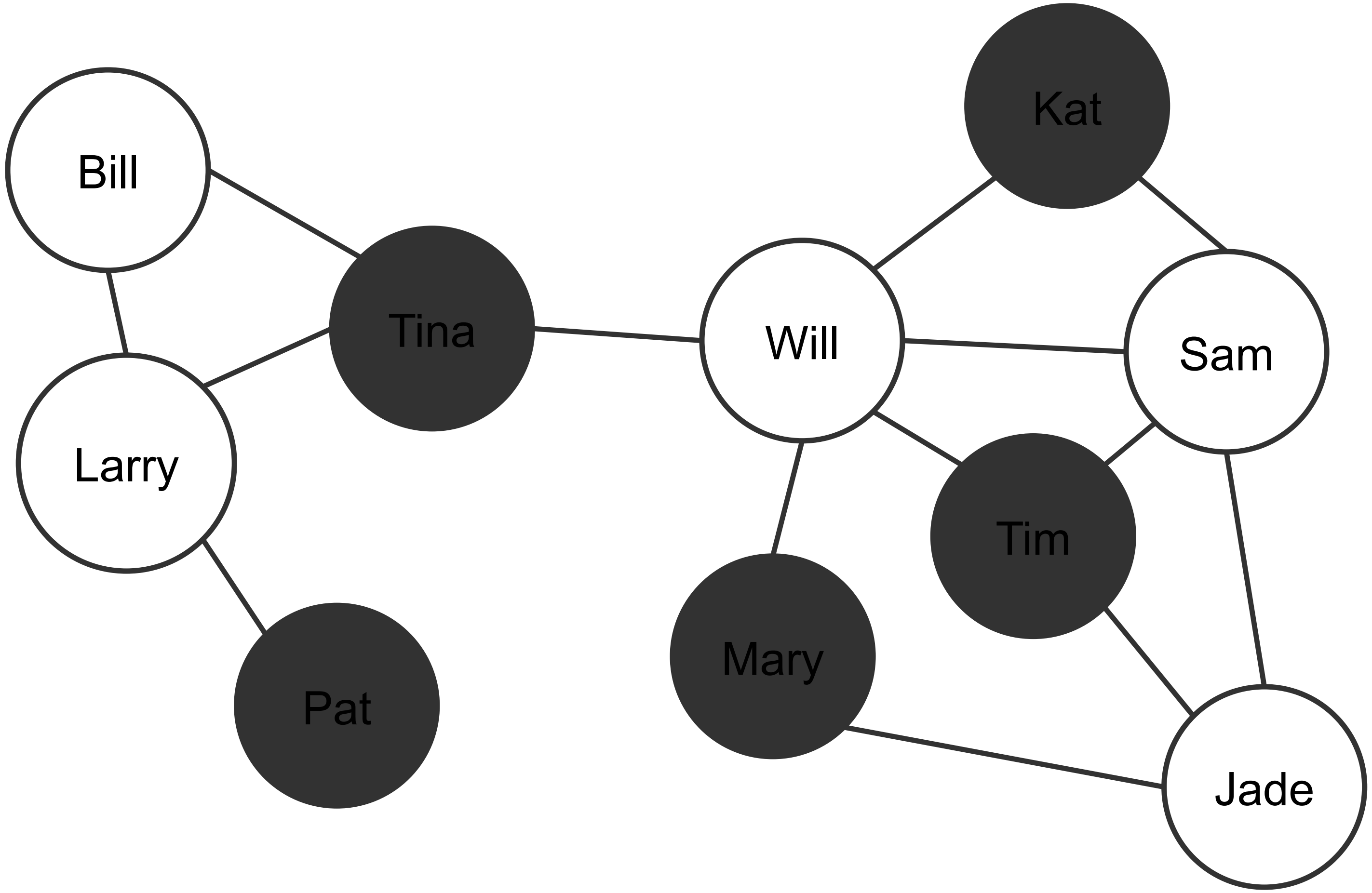

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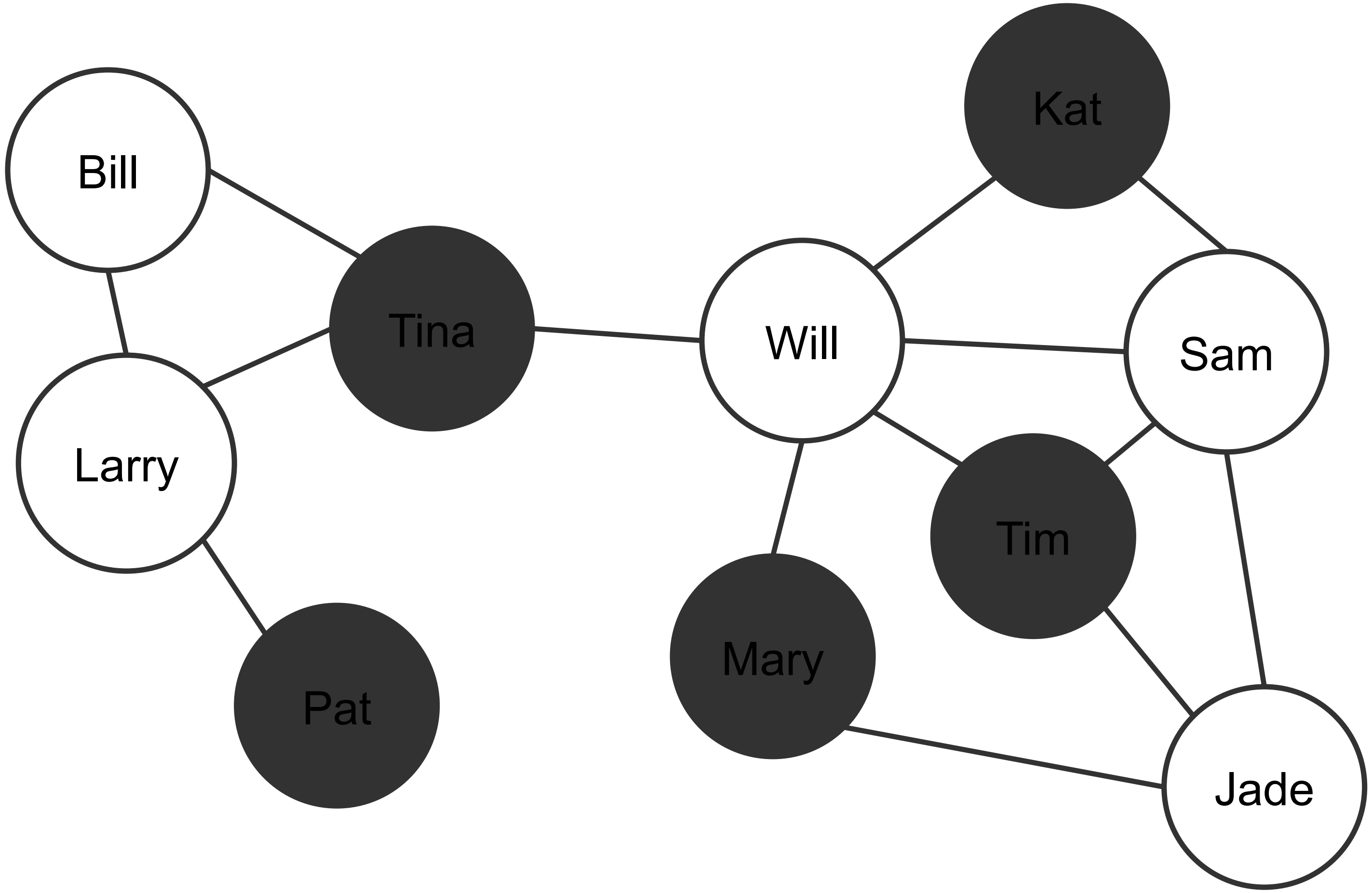

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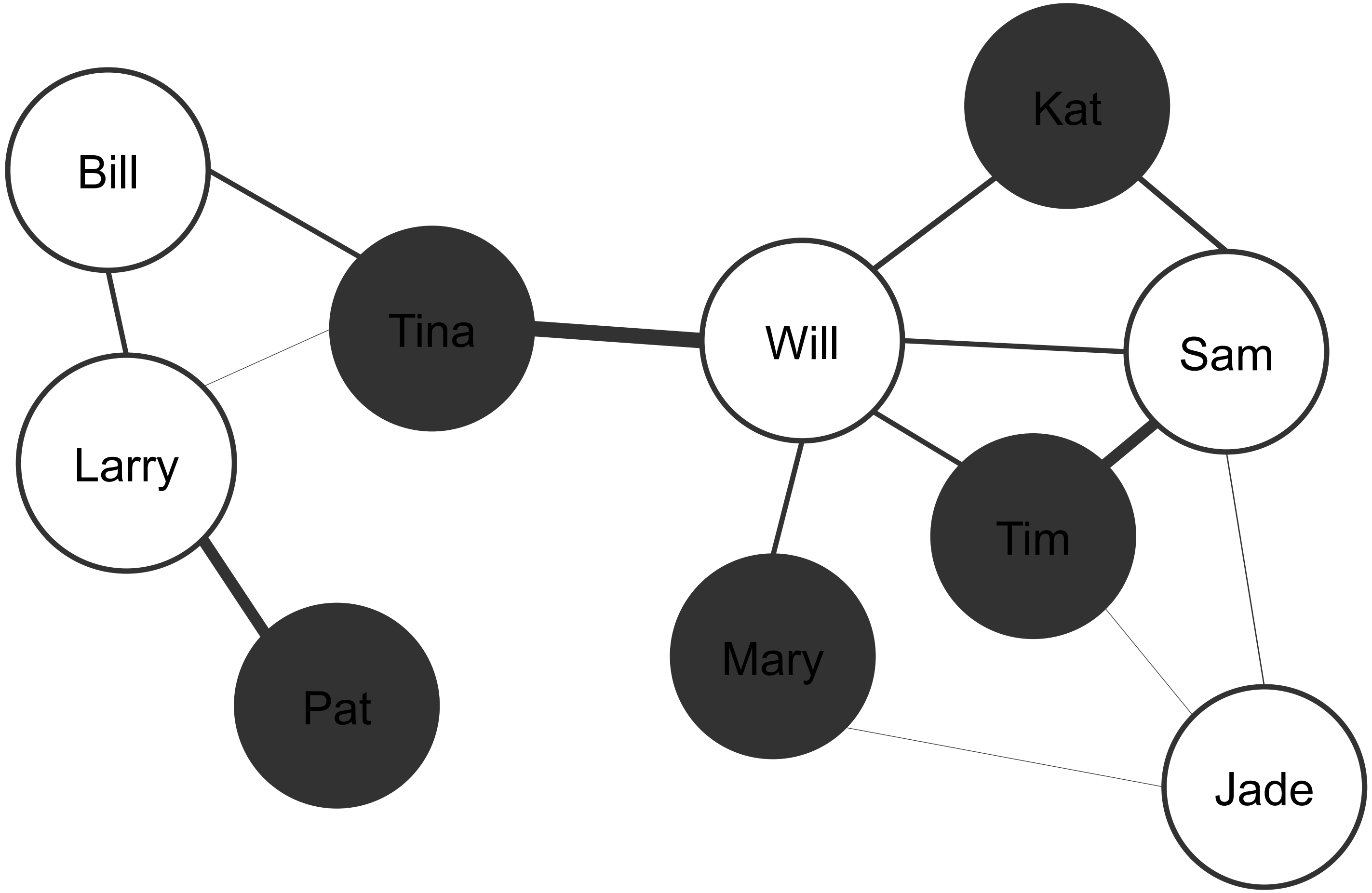

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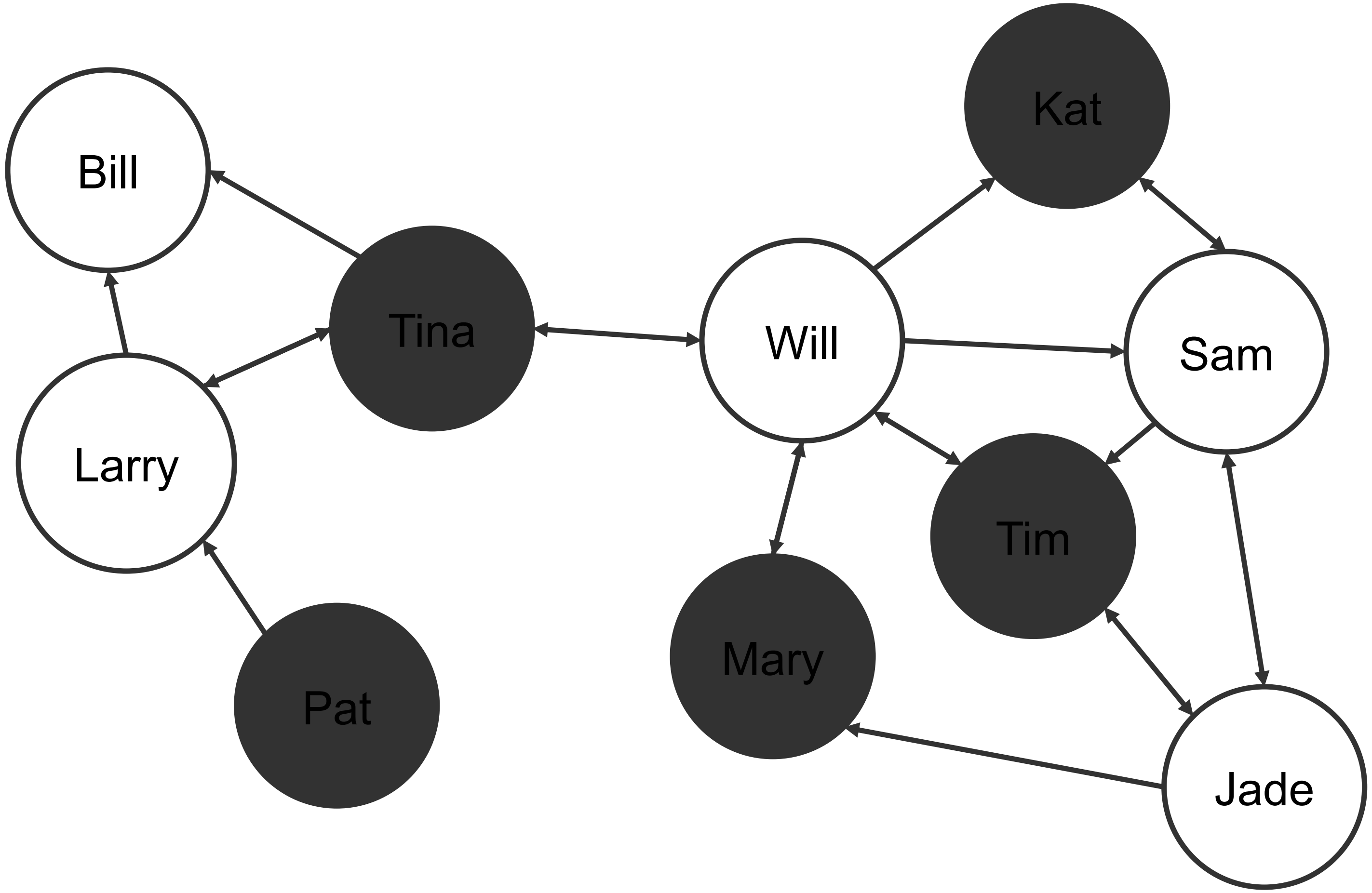
  - **Reciprocity** can also be represented by links.

# Exploring Social Networks



# Graph Network Data Structure

- Data structure is typically square in nature.

| Who Reports Liking Whom? | | | | |
|---|---|---|---|---|
| | Choice: | | | |
| Chooser: | Bill | Tina | Larry | … |
| Bill | – | 1 | 1 | … |
| Tina | 0 | – | 1 | … |
| Larry | 0 | 0 | – | … |
| … | … | … | … | … |

# Graph Network Data Structure

- Data structure doesn’t have to be limited to binary.

| How Does Someone Know Someone (0 = Don’t Know, 1 = Work, 2 = Family) | | | | |
|---|---|---|---|---|
| | **Mark** | **Anthony** | **April** | **Tim** |
| **Mark** | – | 1 | 0 | 2 |
| **Anthony** | 1 | – | 2 | 0 |
| **April** | 1 | 2 | – | 1 |
| **Tim** | 2 | 0 | 1 | – |

# Graph Network Data Structure

- Other differences:
  - **No** independence of observations
  - Samples are rarely desired – try for population of a known network
  - Individuals don't only have to be linked through other individuals
    - Example – schools in a school district

# Modern Adaptations

- Several problems have been addressed by these methods:
  - Spread of disease
  - Marketing of products
  - Fraud detection
- There are also popular cultural themes that have arisen from these methods:
  - Facebook
  - “Six degrees of separation”
  - The Oracle of Bacon

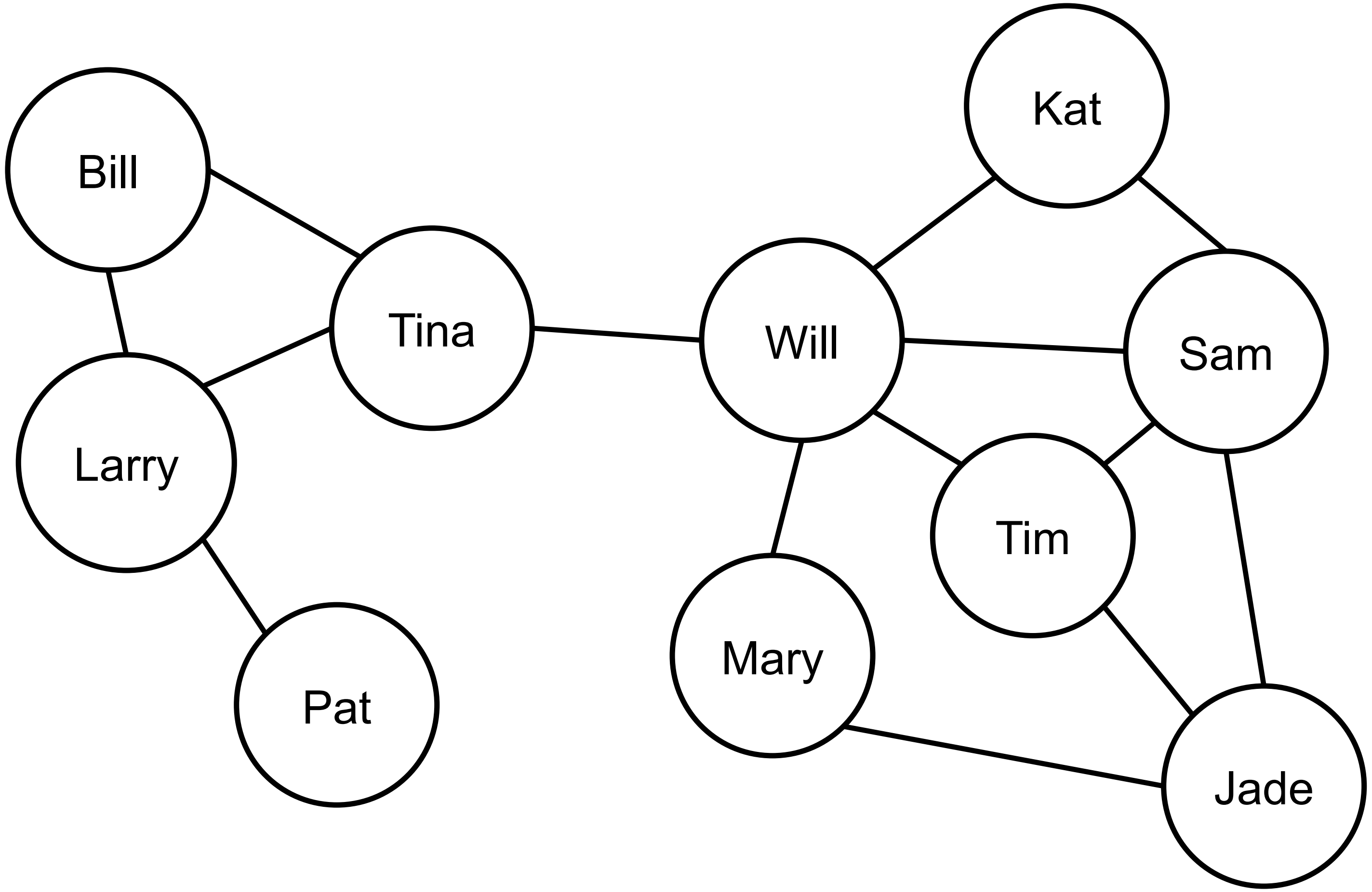
# Social Structure

- There are many different summarizes and important calculations obtained from sociograms.
- Here are a few we will focus on:
  - Subgroups
  - Centers and Closeness
  - Brokers and Bridges
  - Diffusion and Adoption

# Subgroups

- Social networks typically contain dense pockets of individuals.
- These dense pockets are sometimes called **subgroups**.
- If a subgroup is completely separated from the rest of the network, then it is a **cohesive subgroup**.
- Homophily: “Birds of a feather flock together.”
- This can help in the identification of individuals with similar characteristics.
  - Marketing campaigns
  - Fraud detection

# Subgroups



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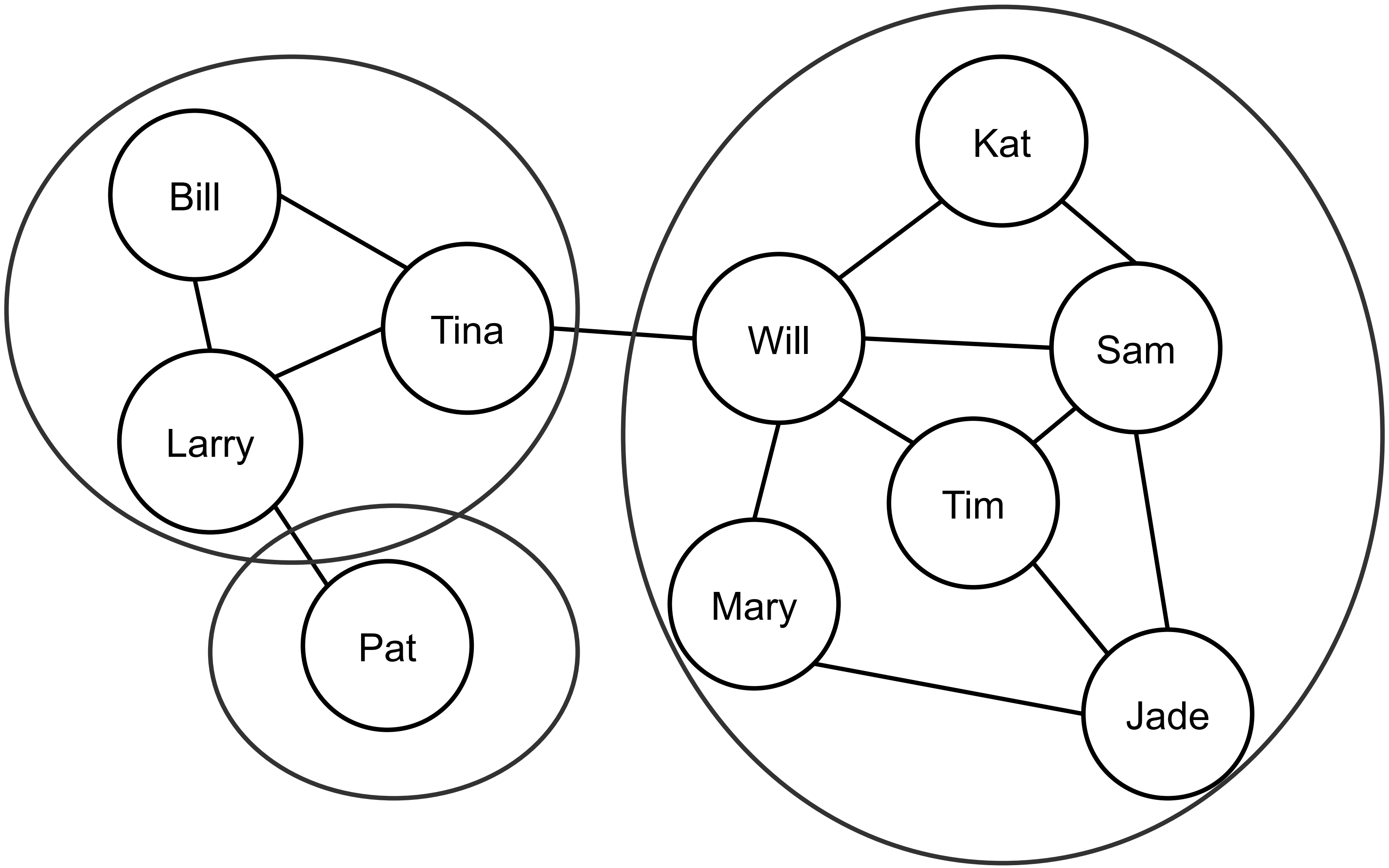

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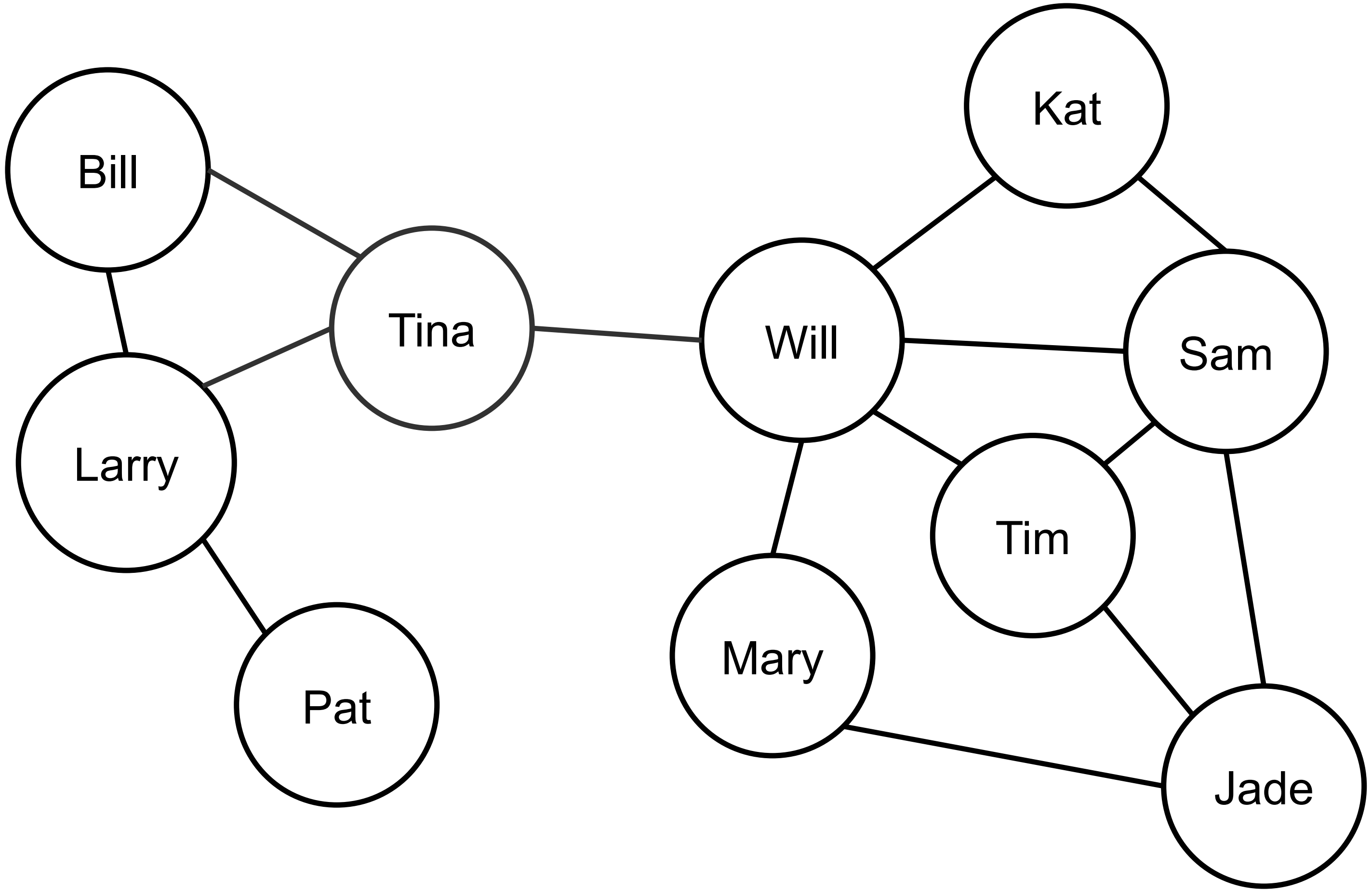
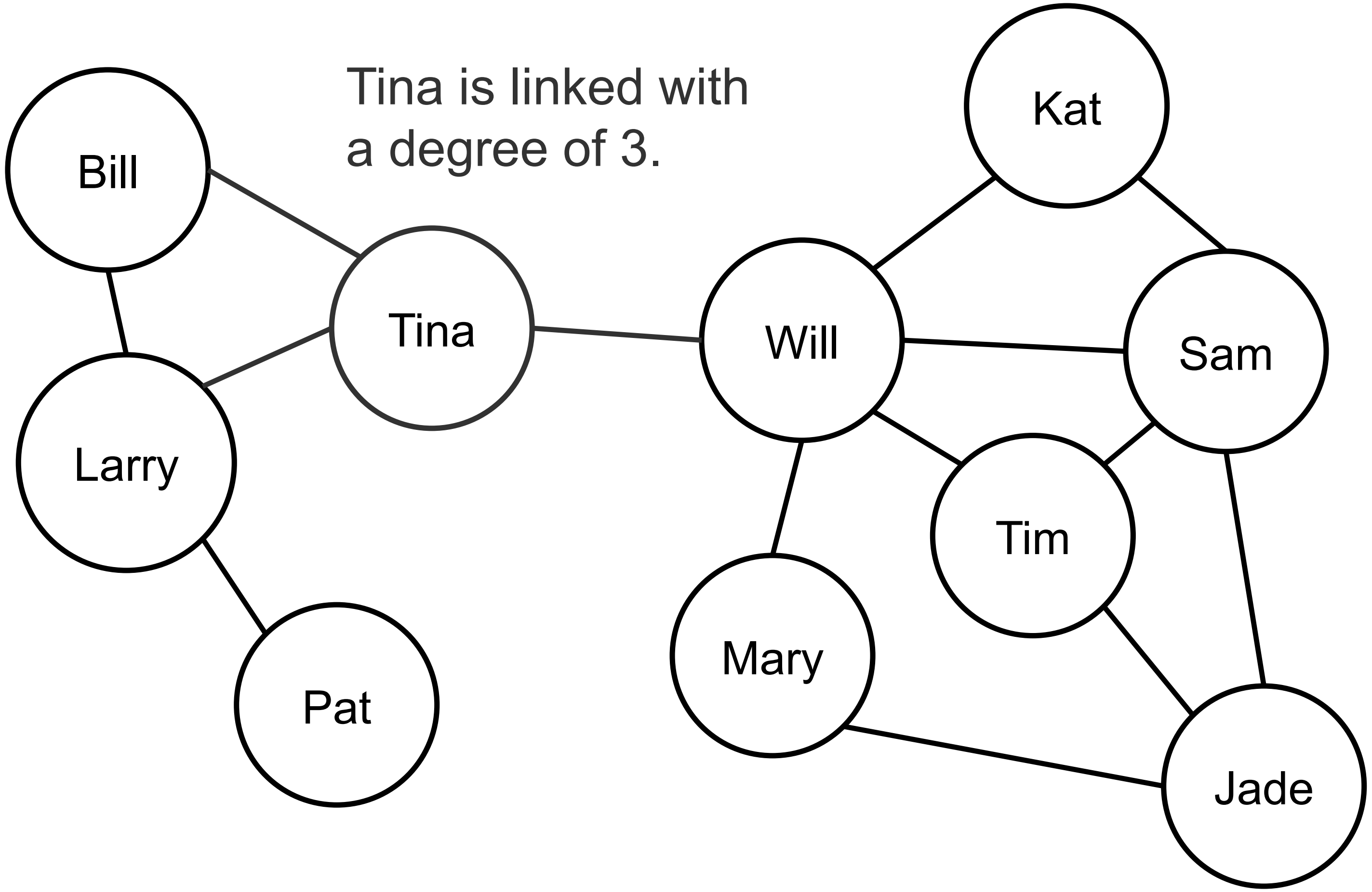
# Degree of Connection



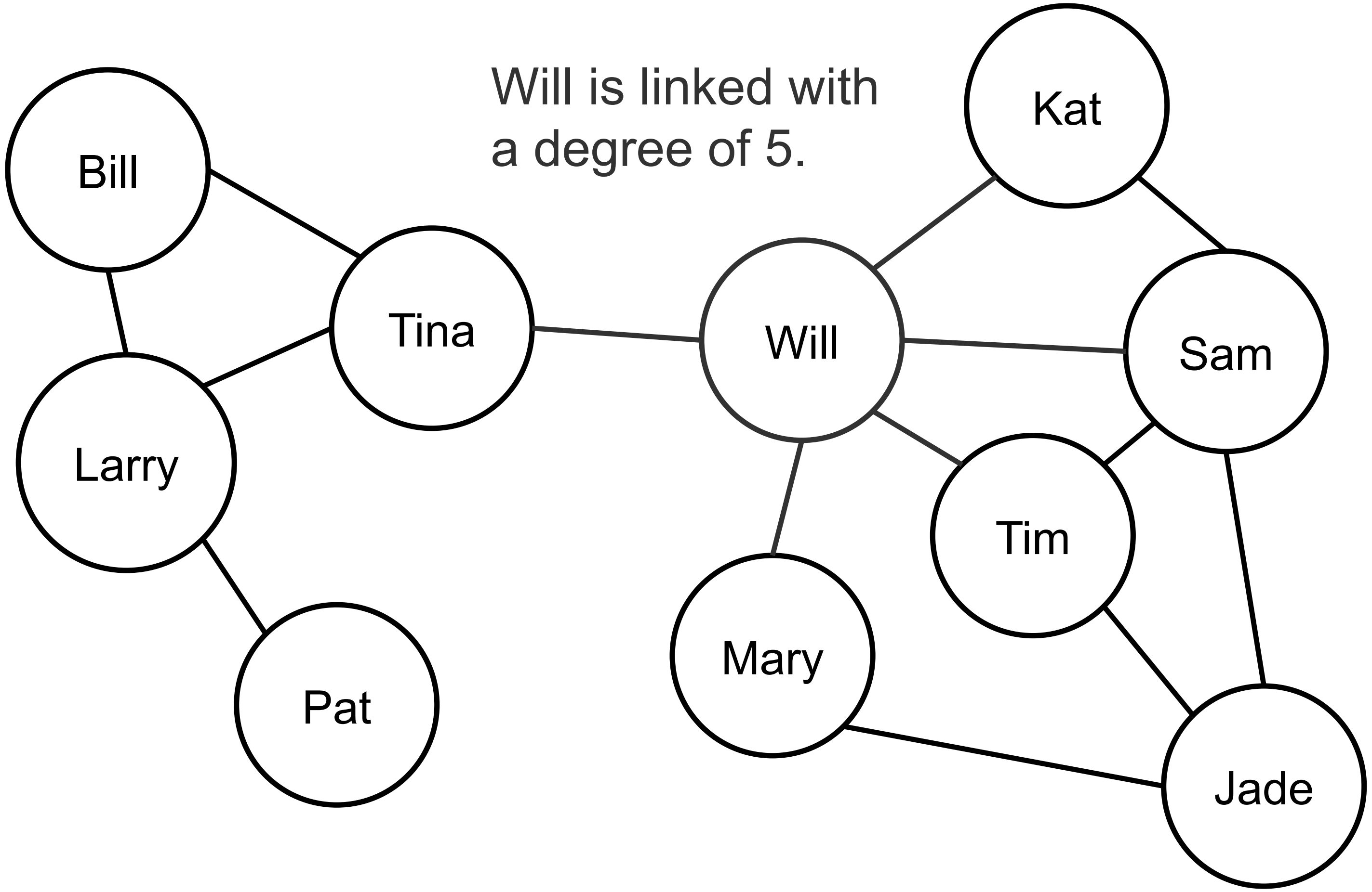
# Degree of Connection

Tina is linked with
a degree of 3.



# Degree of Connection

Will is linked with
a degree of 5.



# Degree of Connection

| Name | Degree of Connection |
|---|---|
| Will | 5 |
| Sam | 4 |
| Jade | 3 |
| Tim | 3 |
| Tina | 3 |
| Larry | 3 |
| Mary | 2 |
| Kat | 2 |
| Bill | 2 |
| Pat | 1 |

# Degree Centrality

- Networks consist of N nodes and n links.
- The maximum degree of each node is N-1.
- Degree centrality ”standardizes” the degree of a node.

$$C_D = \frac{degree}{N - 1}$$

# Degree Centrality

| Name | Degree of Connection | Degree Centrality |
|---|---|---|
| Will | 5 | 0.555 |
| Sam | 4 | 0.444 |
| Jade | 3 | 0.333 |
| Tim | 3 | 0.333 |
| Tina | 3 | 0.333 |
| Larry | 3 | 0.333 |
| Mary | 2 | 0.222 |
| Kat | 2 | 0.222 |
| Bill | 2 | 0.222 |
| Pat | 1 | 0.111 |

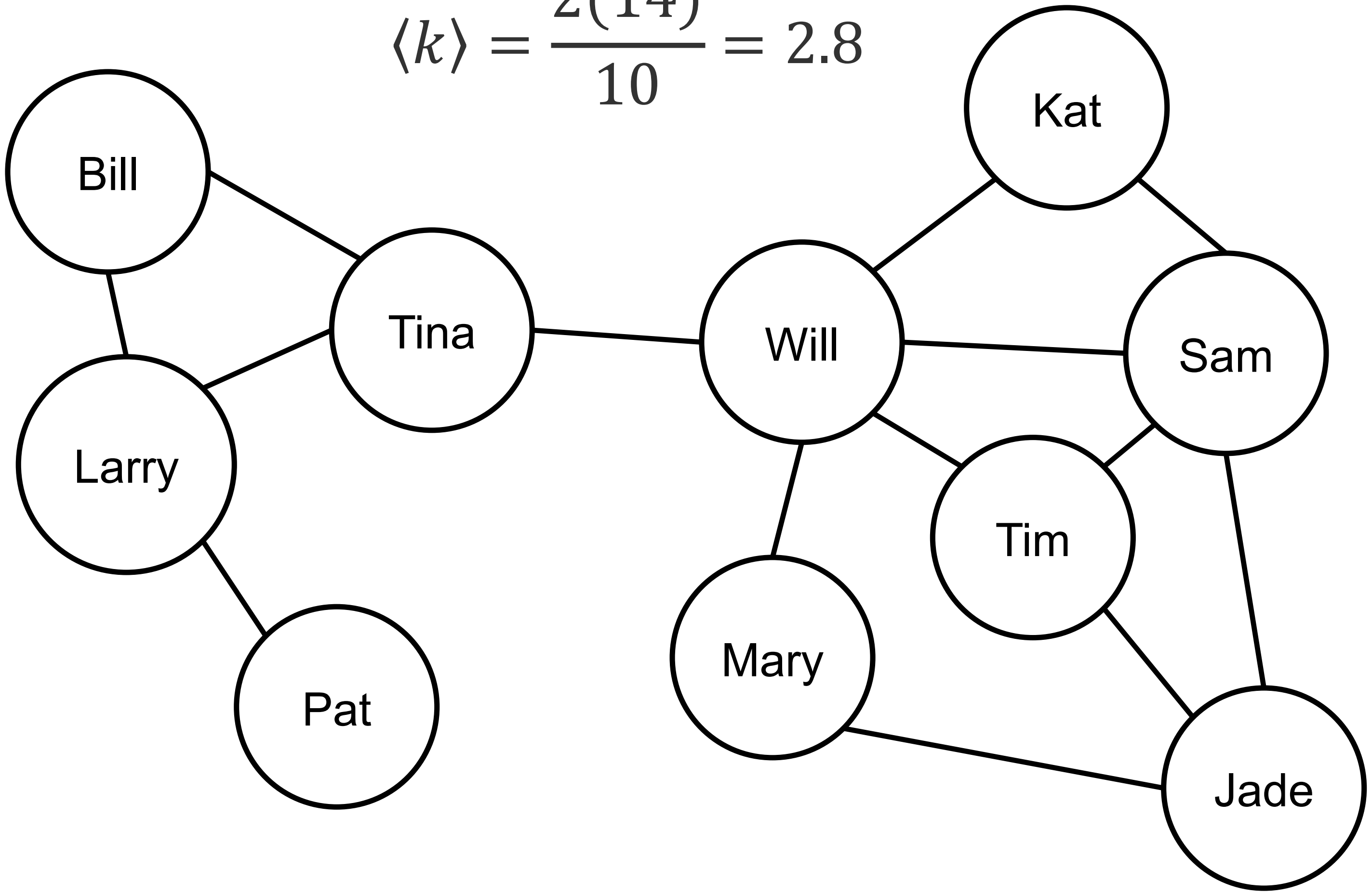
# Average Degree of Graph

- Networks consist of N nodes and n links.
- The average degree of the graph, $\langle k \rangle$, is the following:

$$\langle k \rangle = \frac{2n}{N}$$

# Average Degree of Graph

$$\langle k \rangle = \frac{2(14)}{10} = 2.8$$



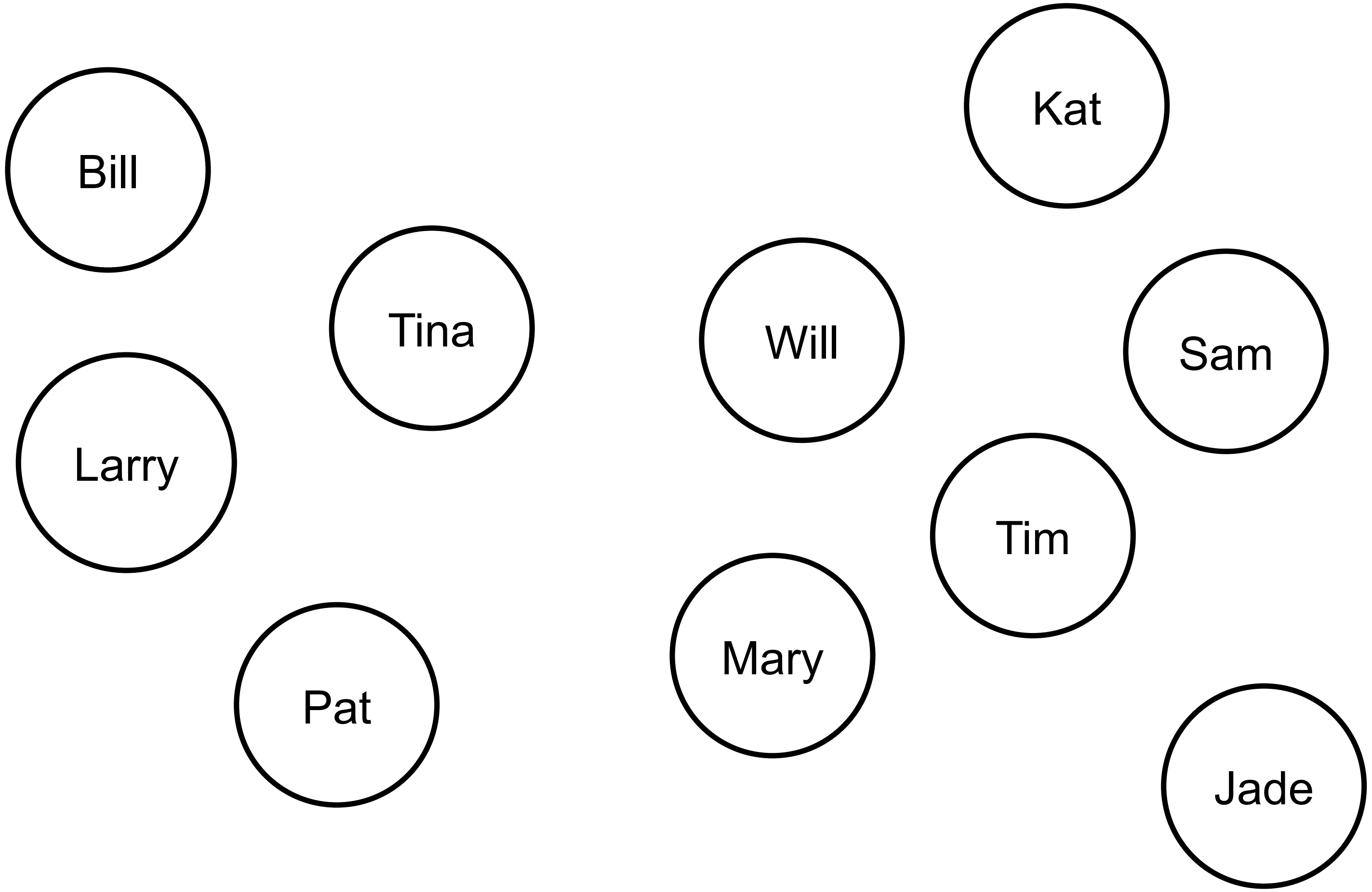
# Density of Graph

- Networks consist of N nodes and n links.
- The density of the graph is the proportion of the number of links actually in the graph compared to the maximum number of links possible in the graph.
- The density of the graph, Δ, is the following:

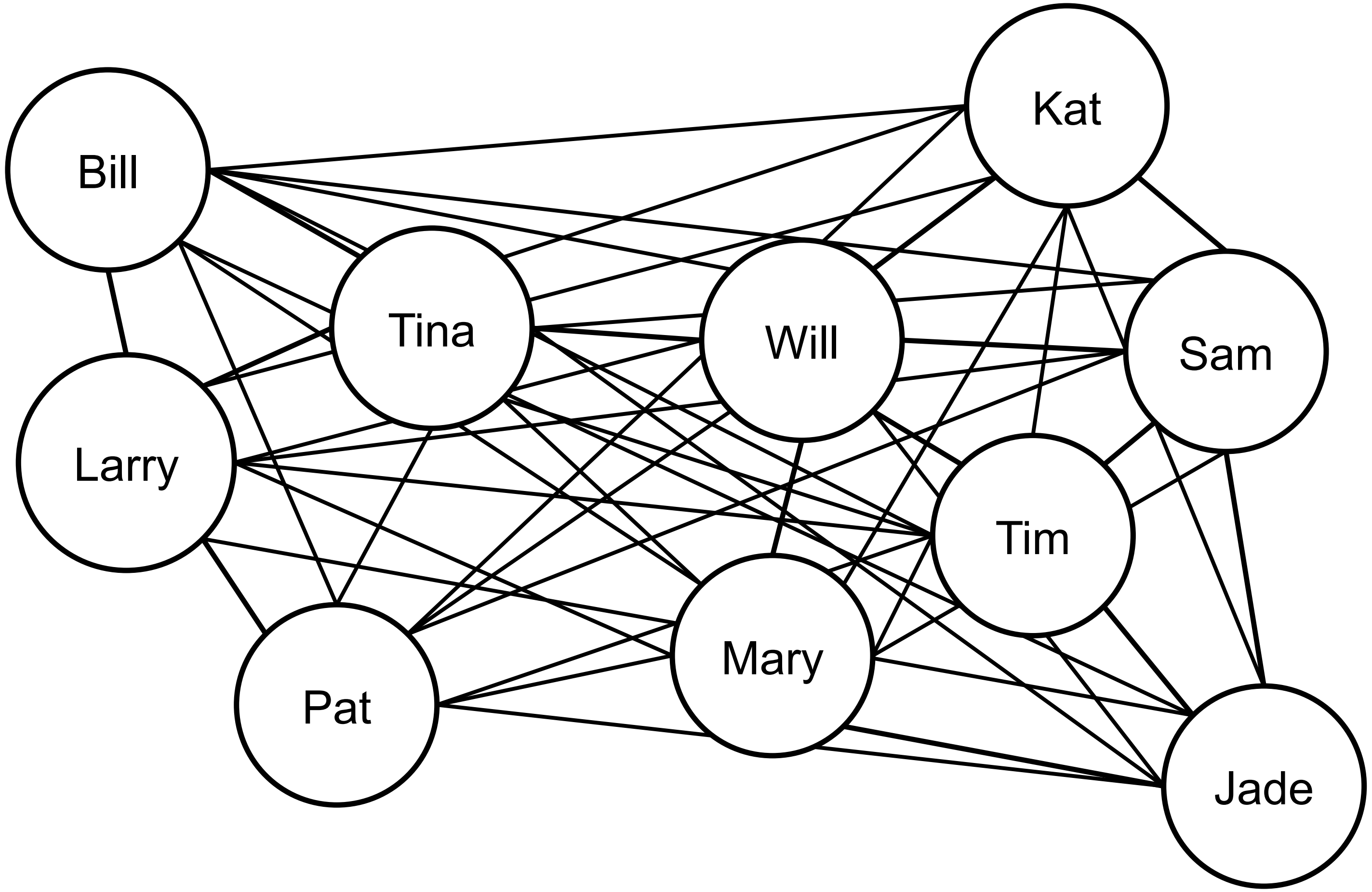
$$\Delta = \frac{2n}{N(N-1)}$$

- This is also called the **connection probability**.

# Density of Graph

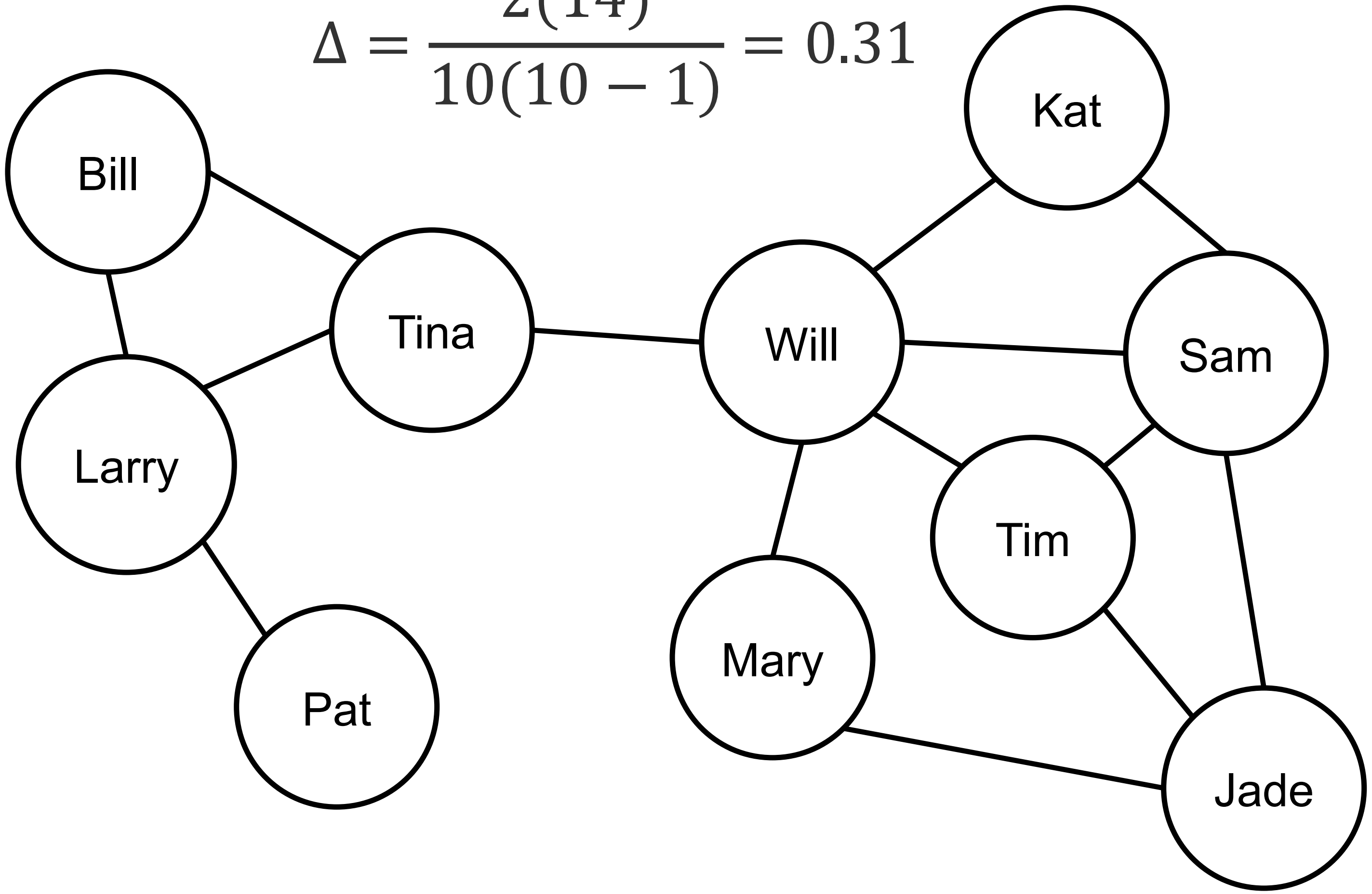


# Density of Graph



# Density of Graph

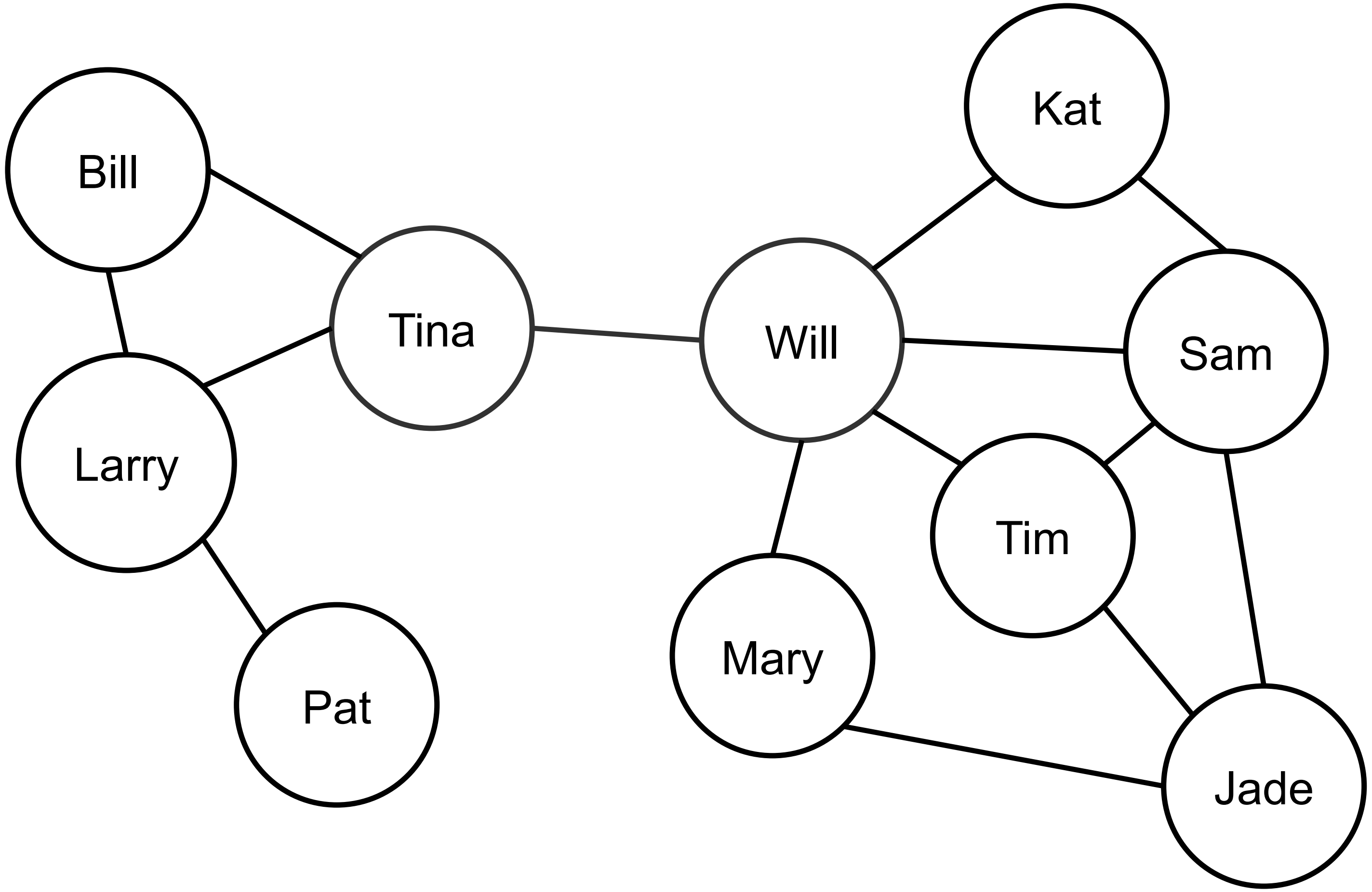
$$\Delta = \frac{2(14)}{10(10-1)} = 0.31$$



# Degree of Separation

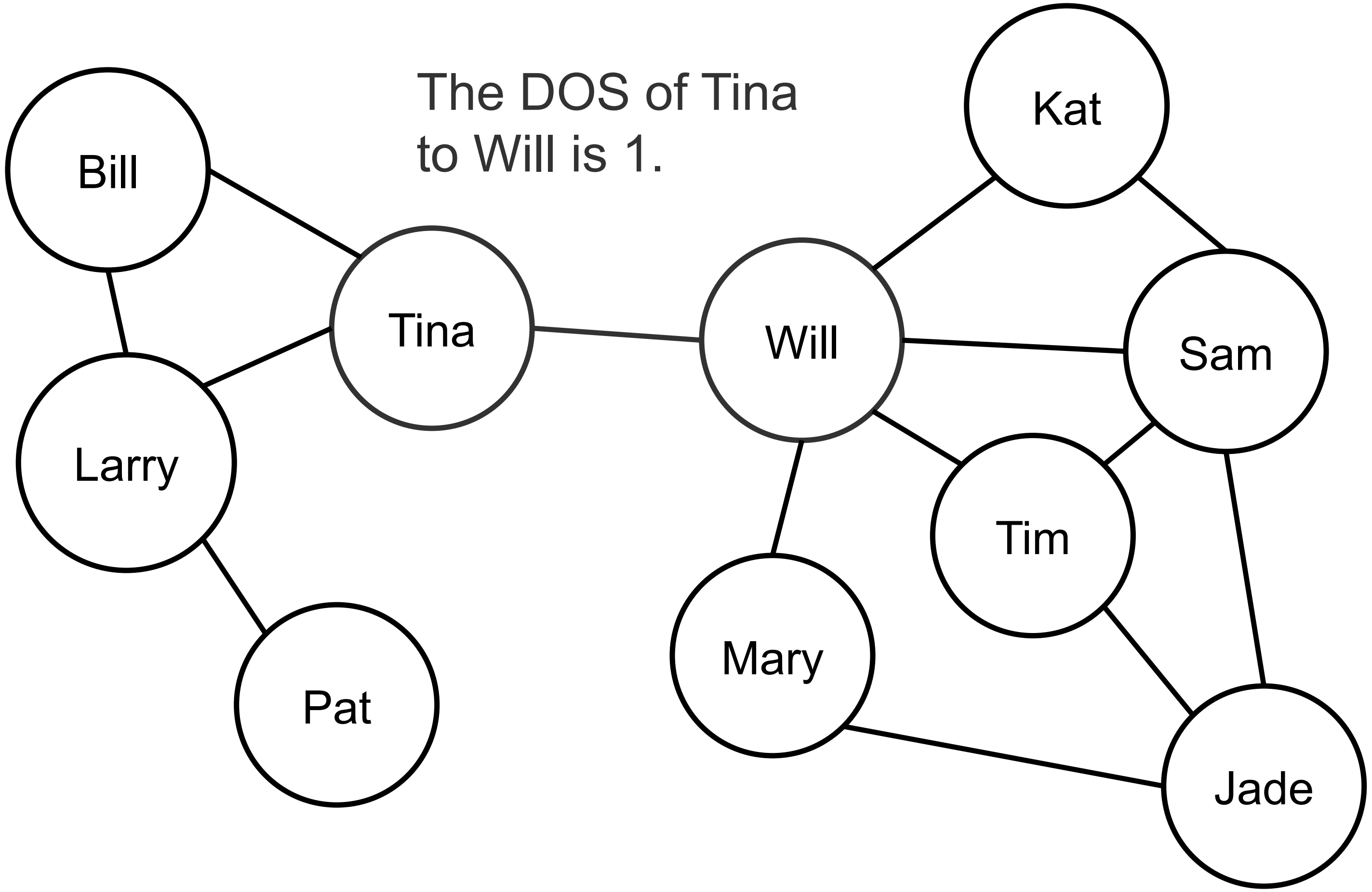
- The degree of connection is one way to measure the center of a network.
- The degree of separation is another way to measure center.
- The degree of connection only focuses on the links for a certain individual, while degree of separation focuses on the value of those links.

# Degree of Separation (DOS)



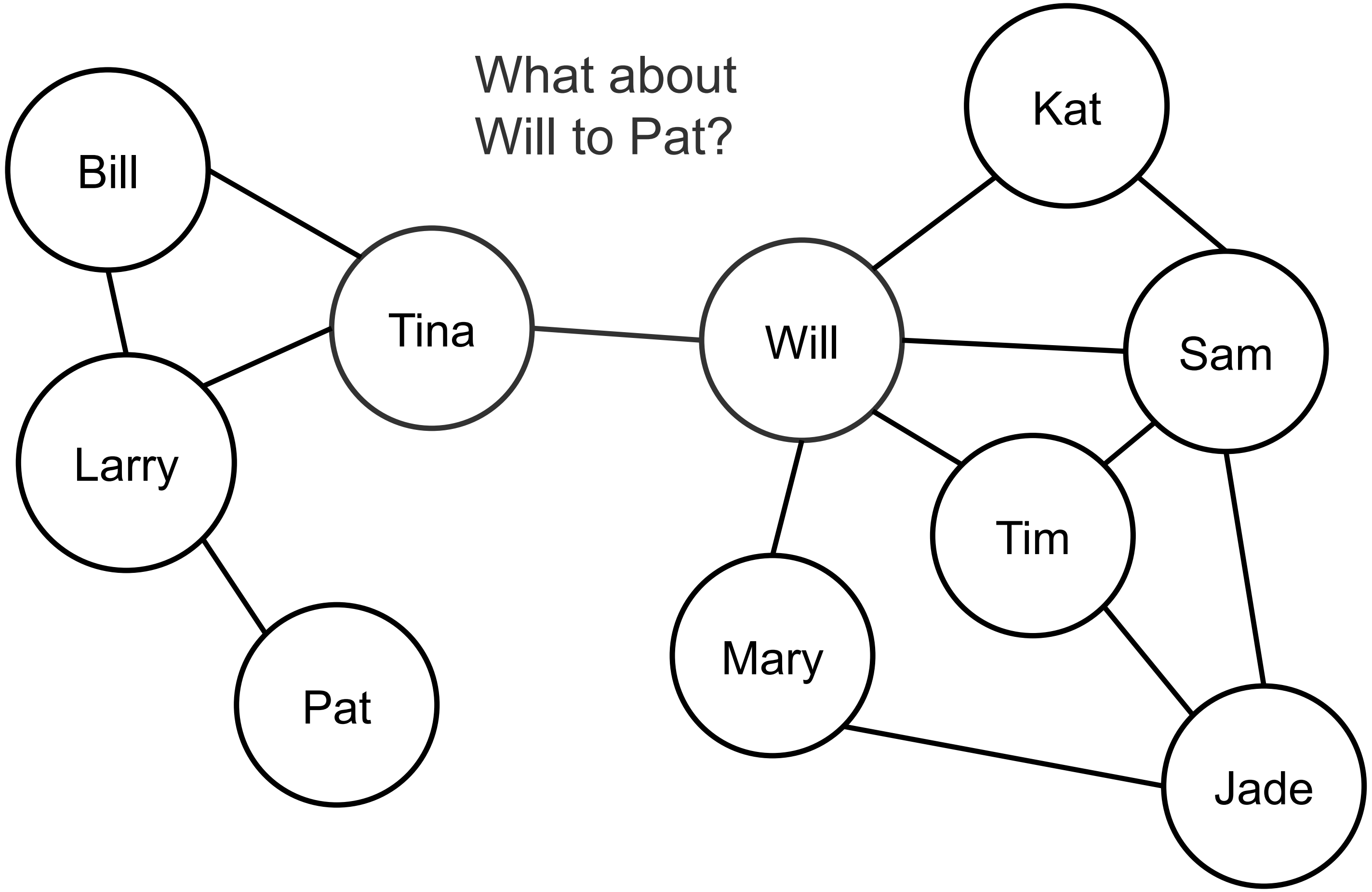
# Degree of Separation (DOS)

The DOS of Tina to Will is 1.

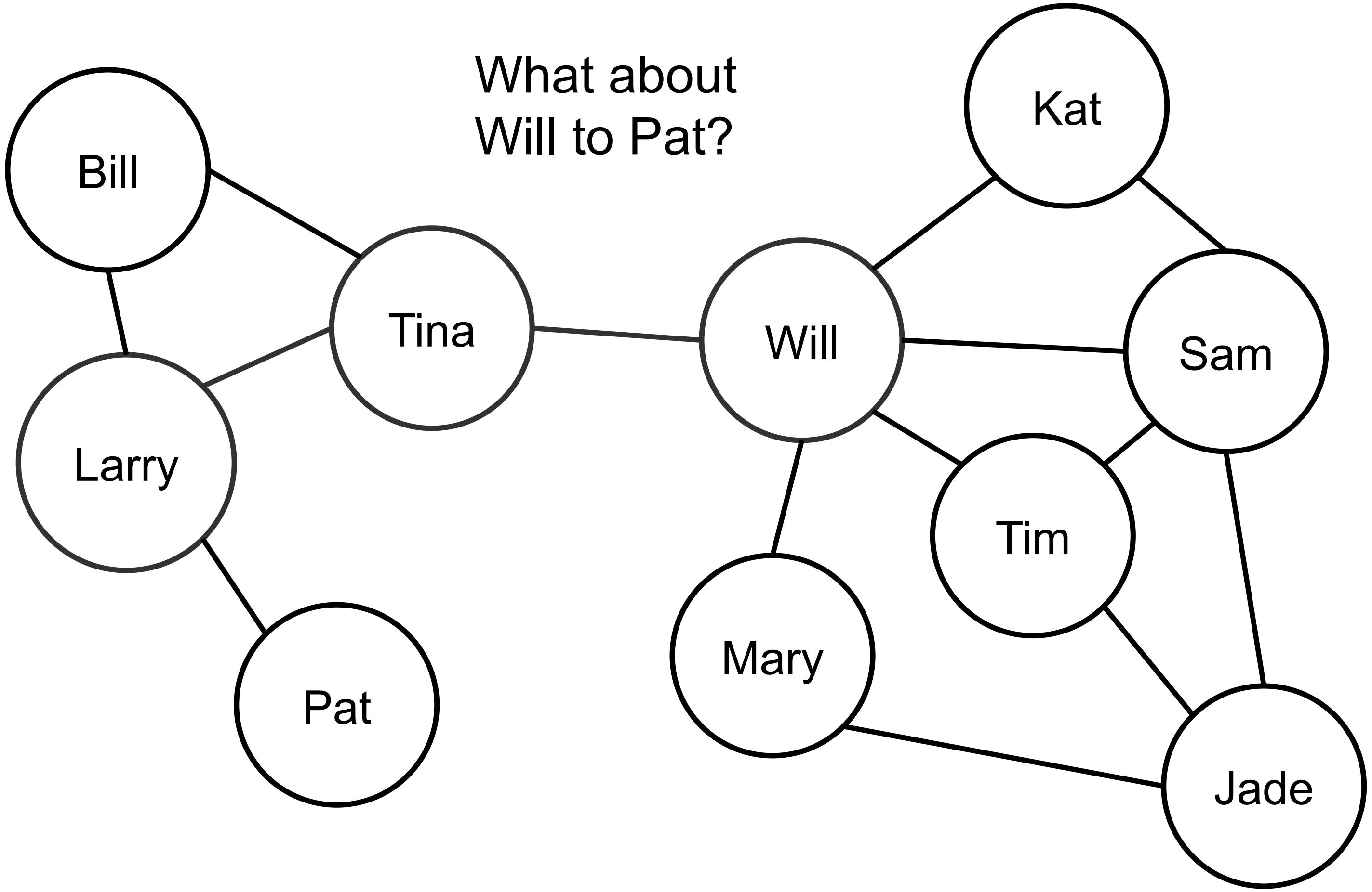


# Degree of Separation (DOS)

What about
Will to Pat?

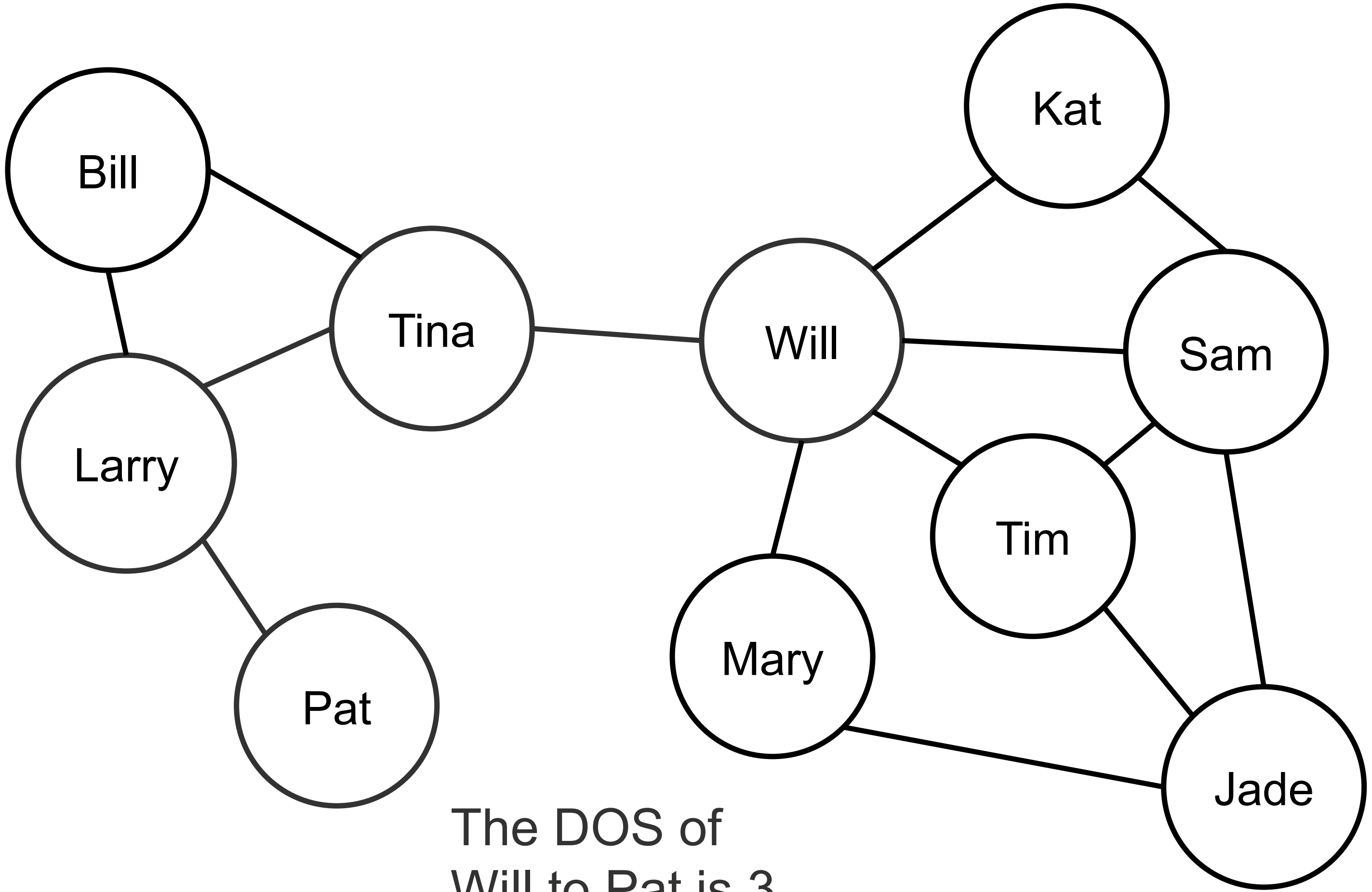


# Degree of Separation (DOS)




What about
Will to Pat?

# Degree of Separation (DOS)




The DOS of
Will to Pat is 3.

# Closeness Centrality

- Closeness centrality is a measure of how well everyone in a network can connect to every other member of the network.
- It is calculated as follows:

$$C_C = \frac{N-1}{\sum_{i=1}^{N-1} DOS_i}$$

# Closeness Centrality

| Name | Closeness Centrality |
|---|---|
| Will | 0.64 |
| Tina | 0.56 |
| Sam | 0.50 |
| Tim | 0.47 |
| Kat | 0.45 |
| Mary | 0.45 |
| Larry | 0.43 |
| Bill | 0.41 |
| Jade | 0.39 |
| Pat | 0.31 |

# Eigenvector Centrality

| | Bill | Larry | Tina | Pat | Will | Kat | Sam | Tim | Jade | Mary |
|---|---|---|---|---|---|---|---|---|---|---|
| **Bill** | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Larry** | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Tina** | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| **Pat** | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Will** | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 |
| **Kat** | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| **Sam** | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| **Tim** | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| **Jade** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 |
| **Mary** | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 |

# Eigenvector Centrality

- A node is high in eigenvector centrality if it is connected to many other nodes who are themselves well connected.
- A node’s centrality is dependent on the centrality of adjacent nodes.
- These nodes would be considered influential – closely related to **diffusion** and **adoption**.

# Eigenvector Centrality

- Eigenvector centrality for each node is simply calculated as the proportional eigenvector values of the eigenvector with the largest eigenvalue.

$$\boldsymbol{Ax} = \boldsymbol{\lambda x}$$

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

Find largest eigenvalue

# Eigenvector Centrality

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

Find corresponding eigenvector

# Eigenvector Centrality

| Name | Scaled Eigenvector Centrality |
|---|---|
| Will | 1.00 |
| Sam | 0.94 |
| Tim | 0.80 |
| Jade | 0.69 |
| Kat | 0.59 |
| Mary | 0.52 |
| Tina | 0.43 |
| Larry | 0.21 |
| Bill | 0.19 |
| Pat | 0.06 |

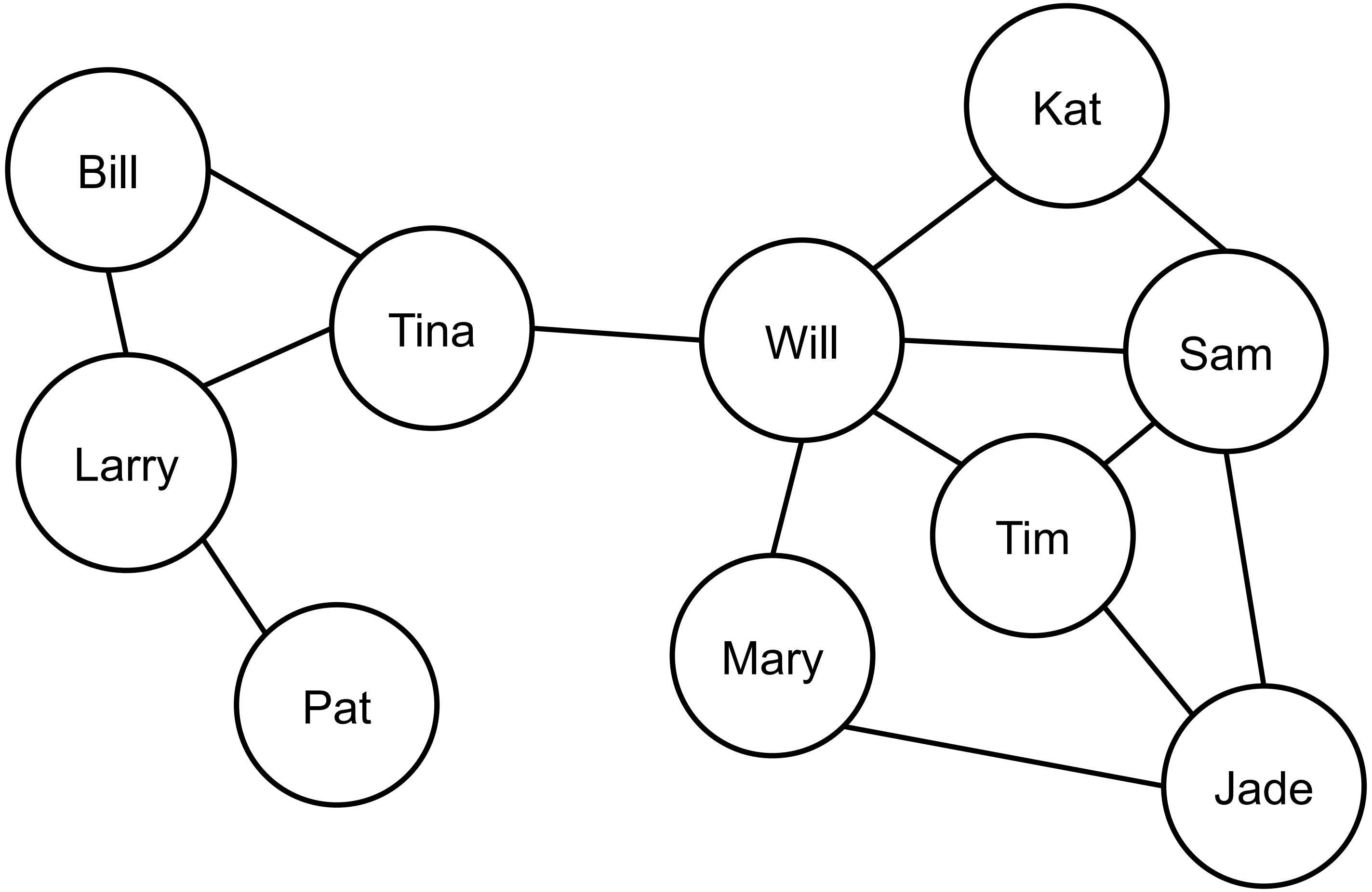
# Social Structure

- There are many different summarizes and important calculations obtained from sociograms.
- Here are a few we will focus on:
  - Subgroups
  - Centers and Closeness
  - Brokers and Bridges
  - Diffusion and Adoption

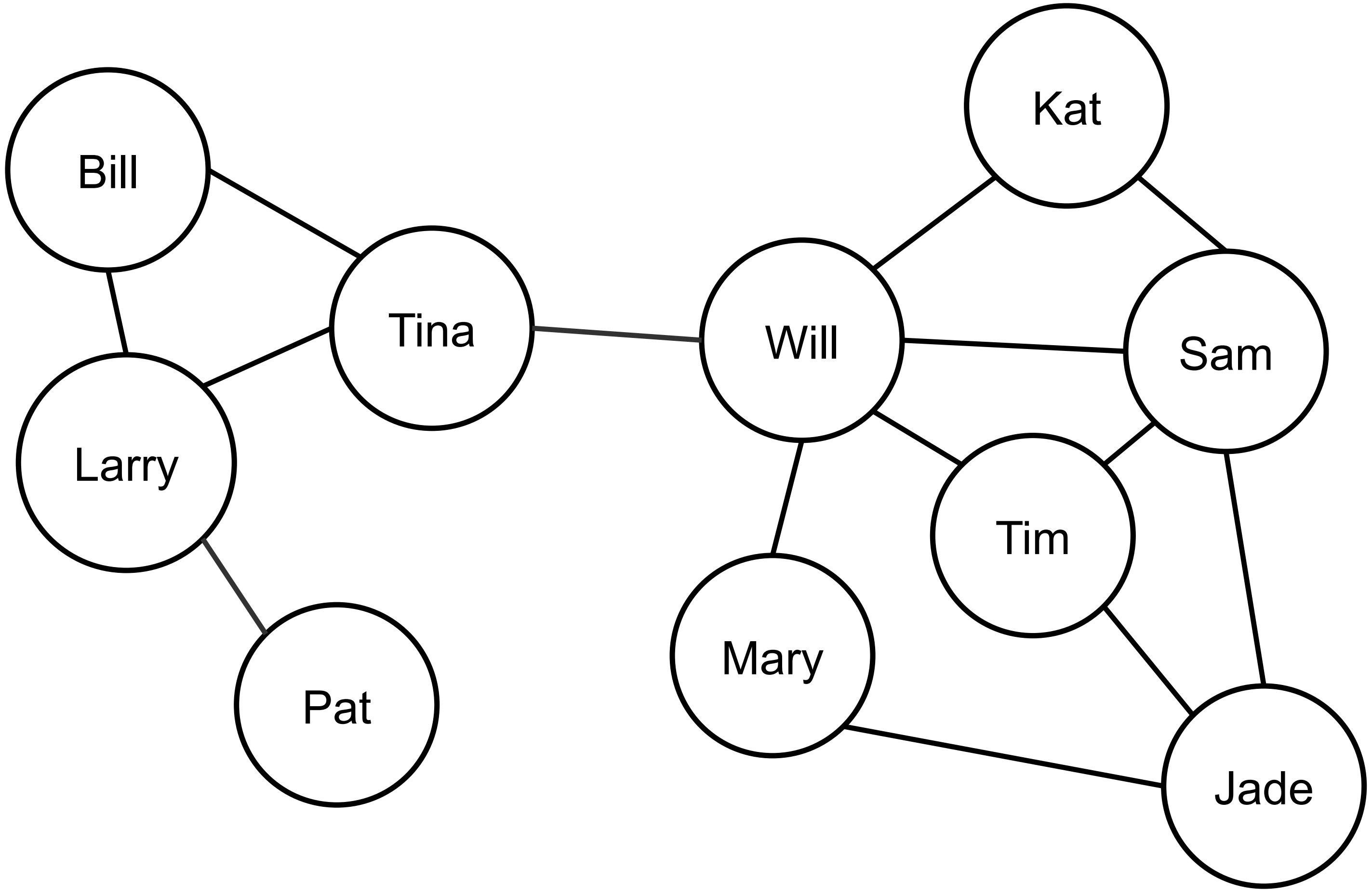
# Different Links

- Not only are number of links important, but the kind of link is extremely important as well.
- Links with individuals who are linked themselves is not as strong as links with individuals who are not linked together.
- Links within a subgroup yield little new information compared to links with other subgroups.
- A **bridge** is a link whose removal increases the number of isolated nodes.

# Bridge



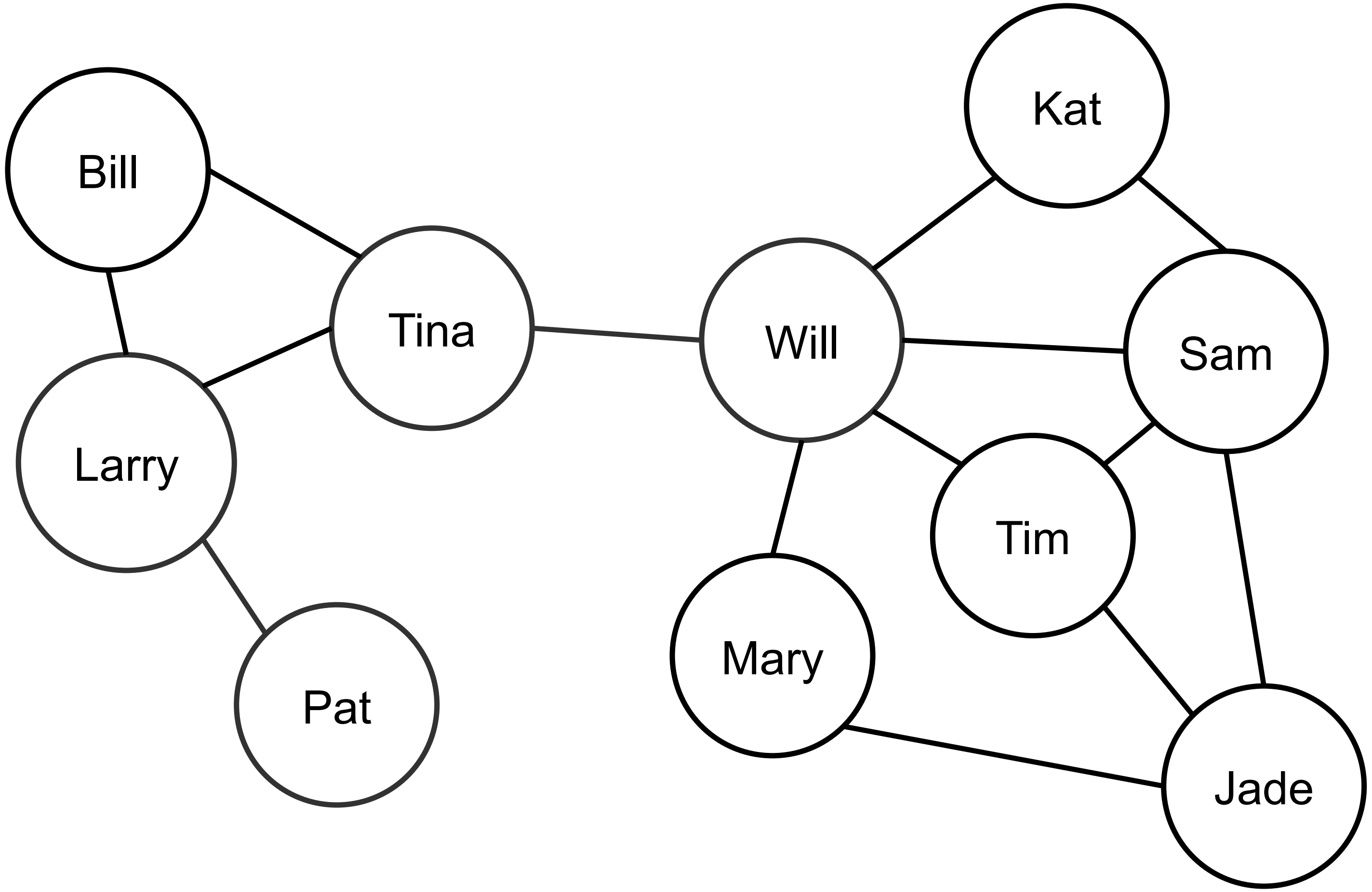
# Bridge



# Brokers

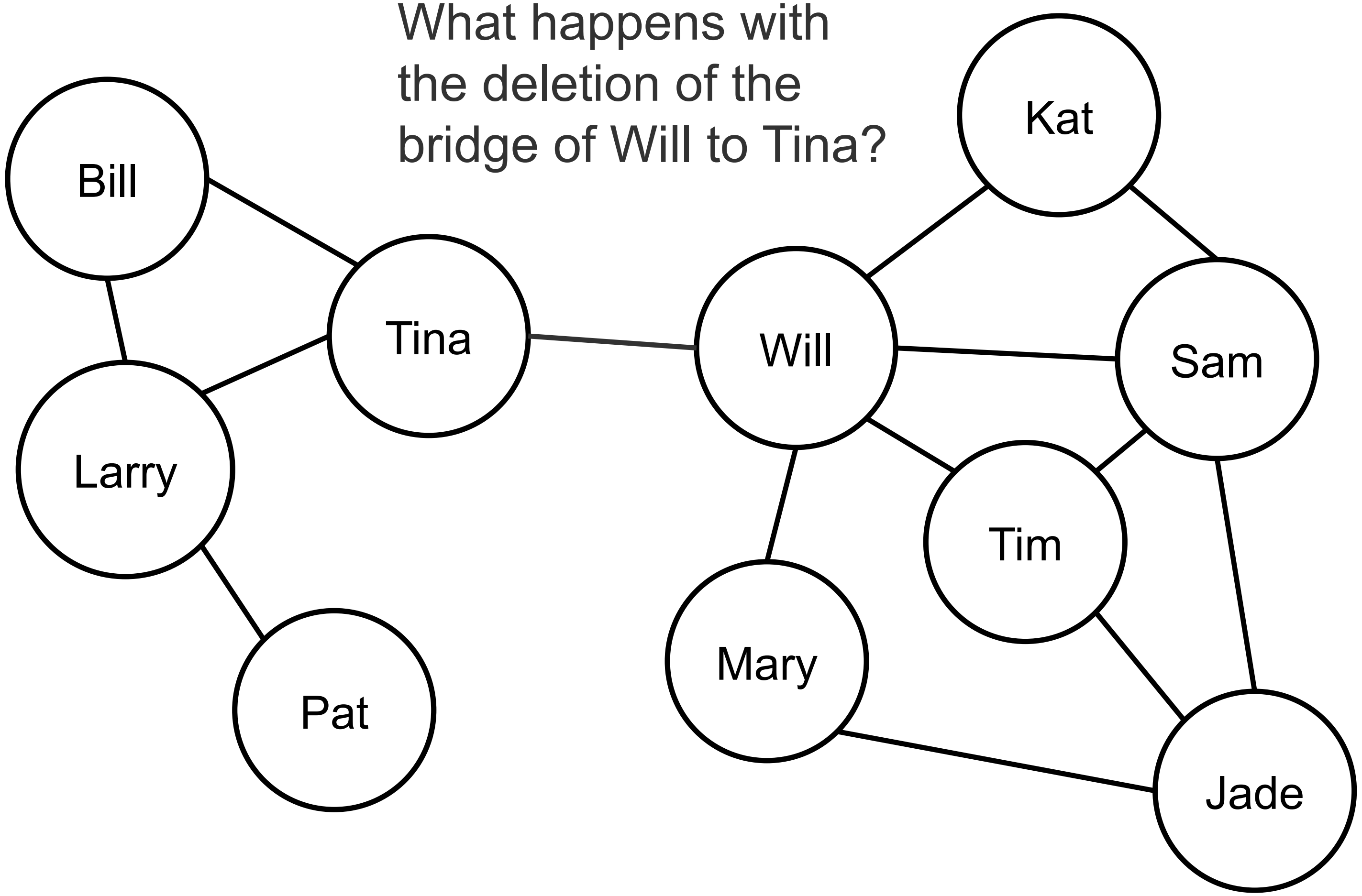
- These bridges are important because they are a potential bottleneck of information.
- The individuals that are connected to these bridges are called **brokers** because they facilitate the information between the two sides of the bridge.
- By eliminating either the bridge or the broker, the spread of information across the network becomes limited.
- Important Applications:
  - Fraud detection
  - Disease contamination
  - Marketing campaigns

# Brokers

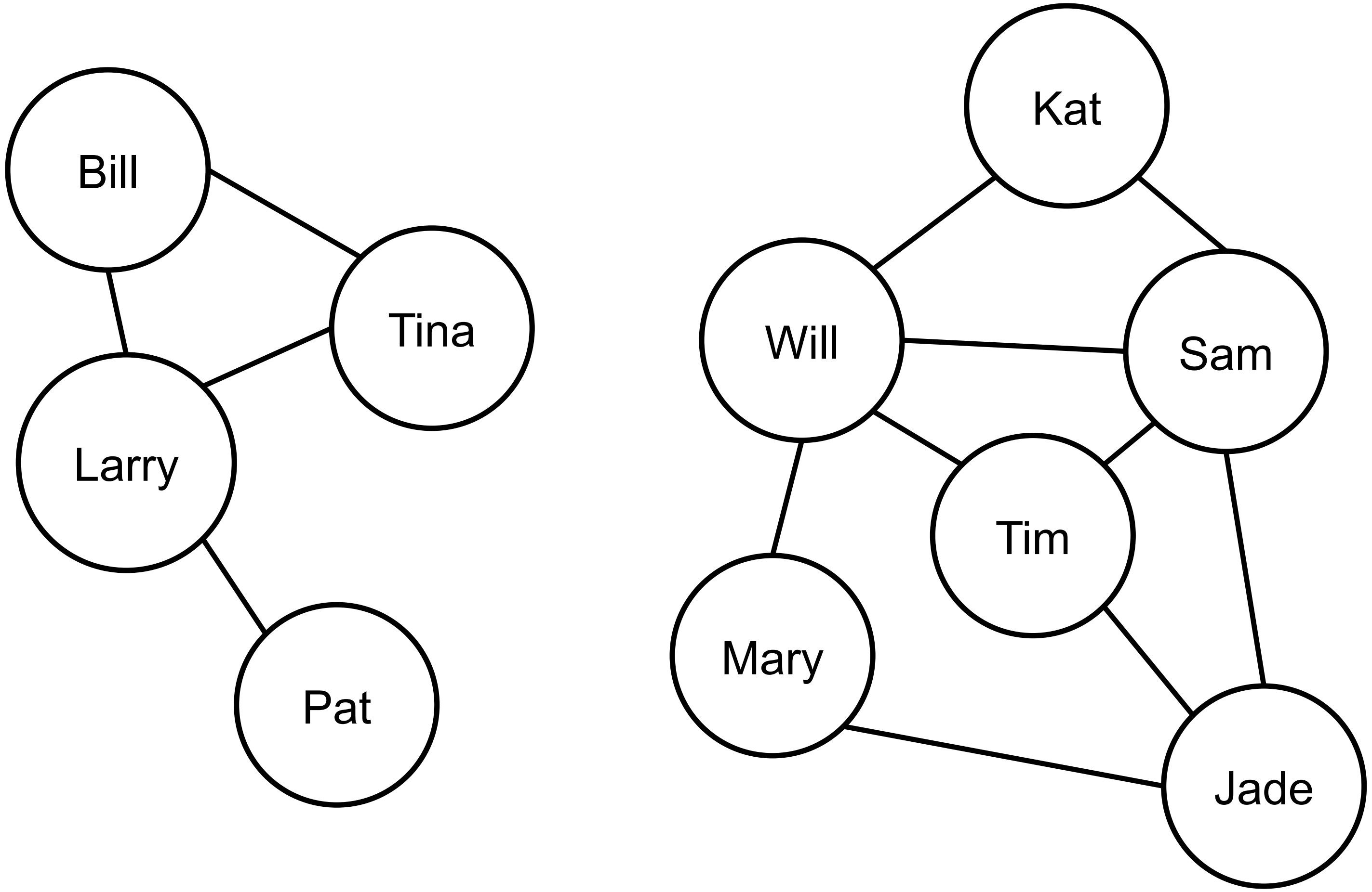


# Bridge Elimination

What happens with the deletion of the bridge of Will to Tina?

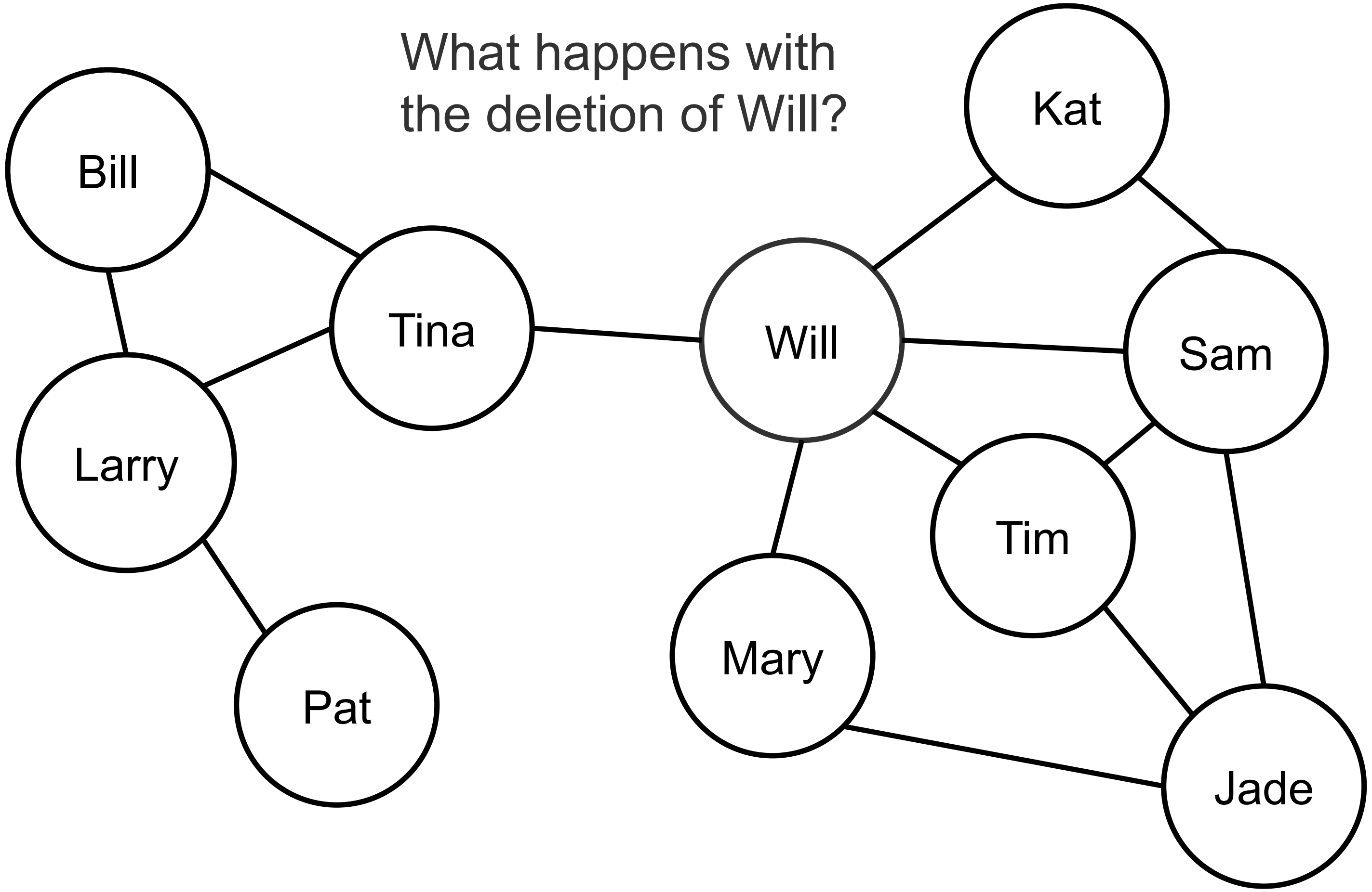


# Bridge Elimination

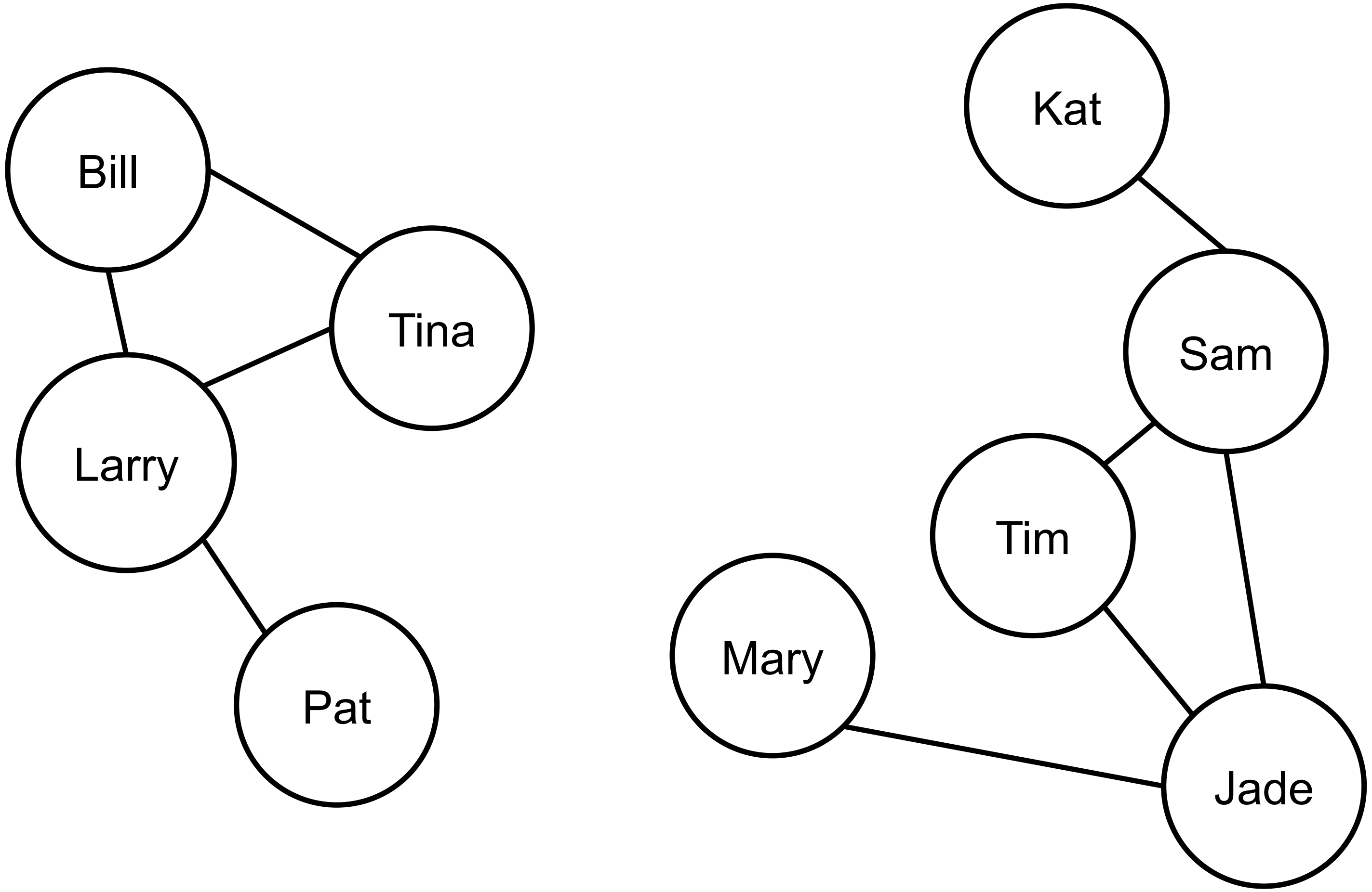


# Broker Elimination

What happens with
the deletion of Will?



# Broker Elimination



# Social Structure

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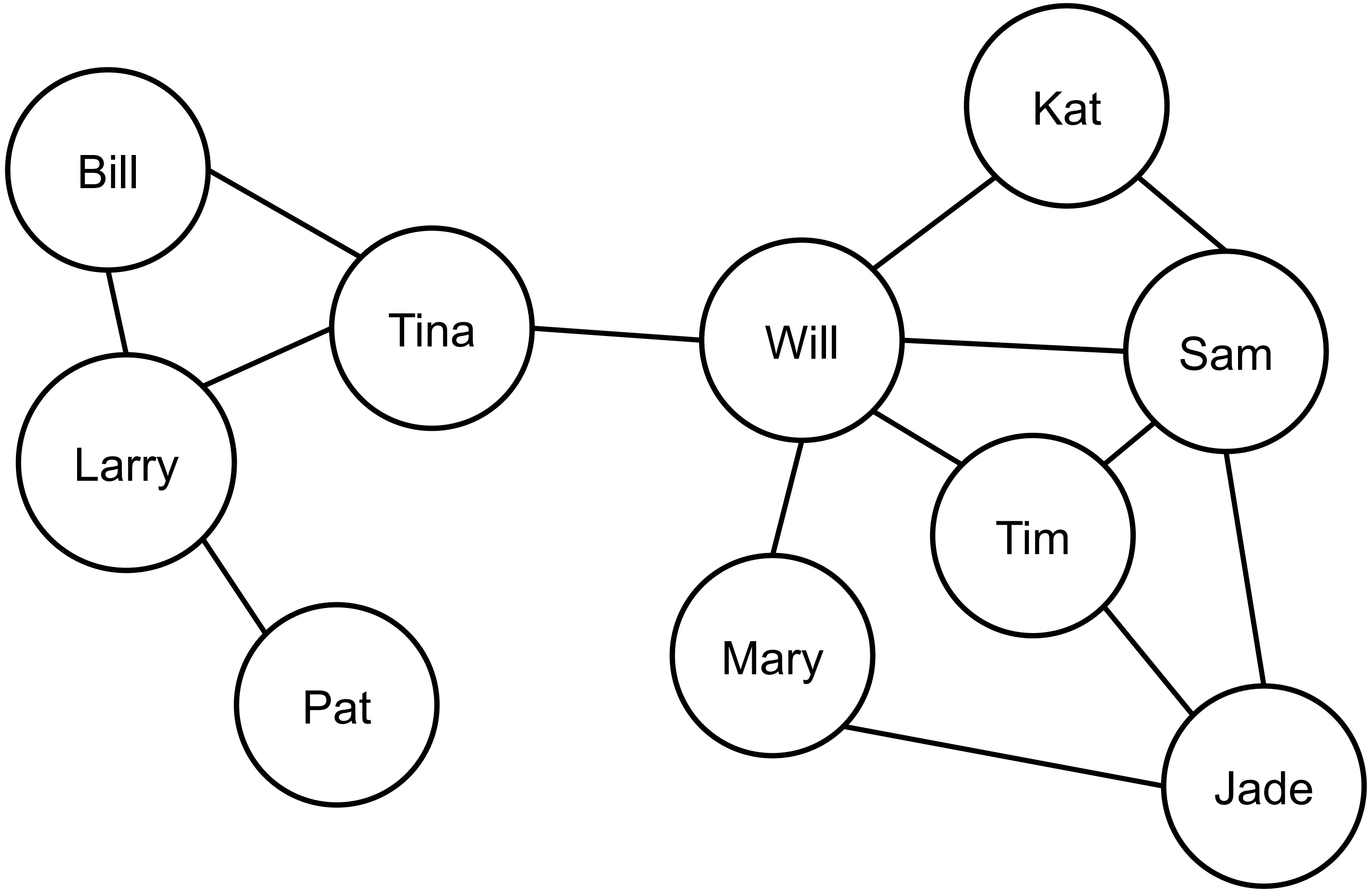
  - Brokers and Bridges
  - Diffusion and Adoption

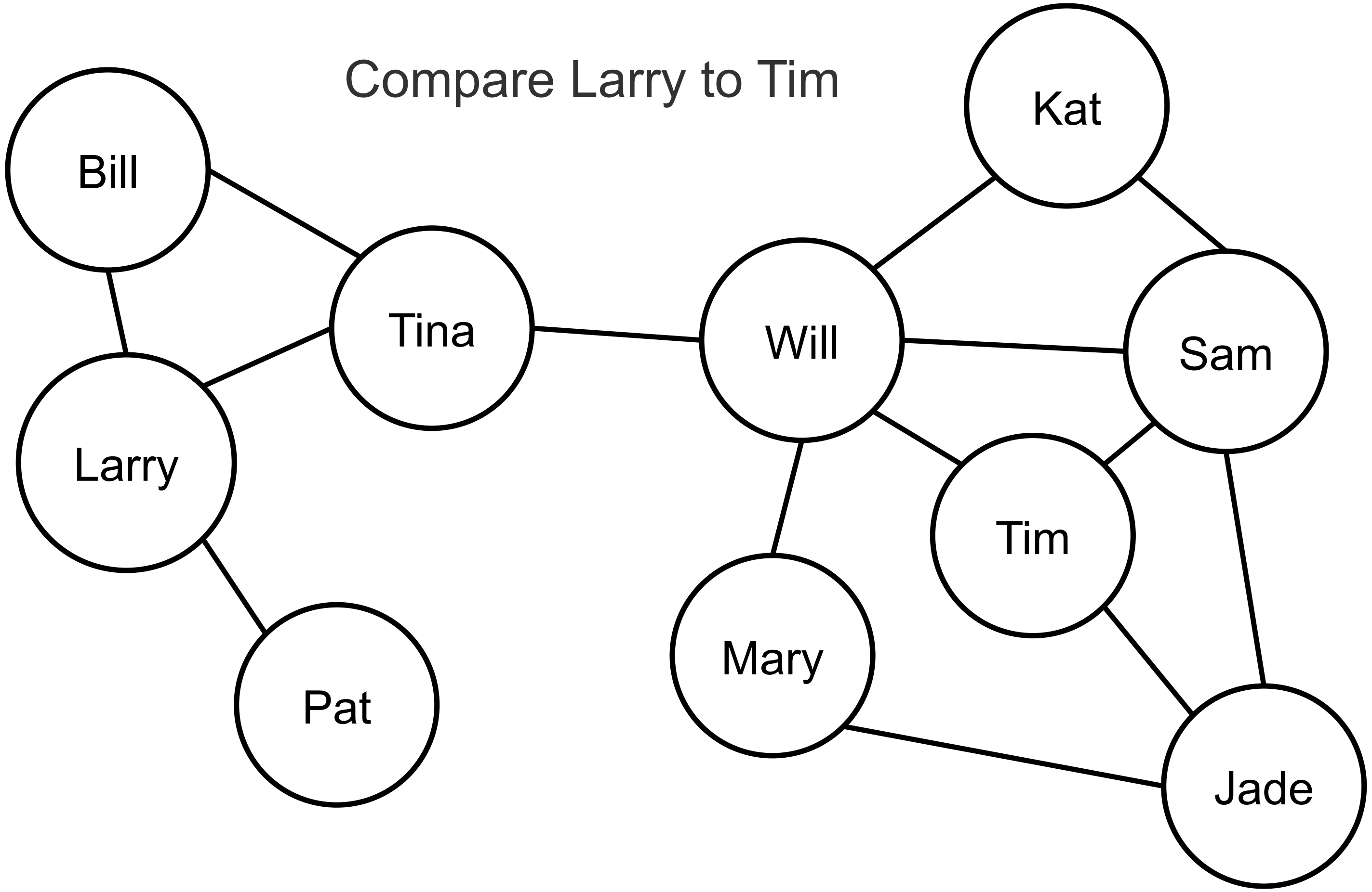
# Diffusion and Adoption

- Diffusion and adoption add a sense of time to a sociogram.
- How long does it take for the entire network to **adopt** an idea based on initial location?

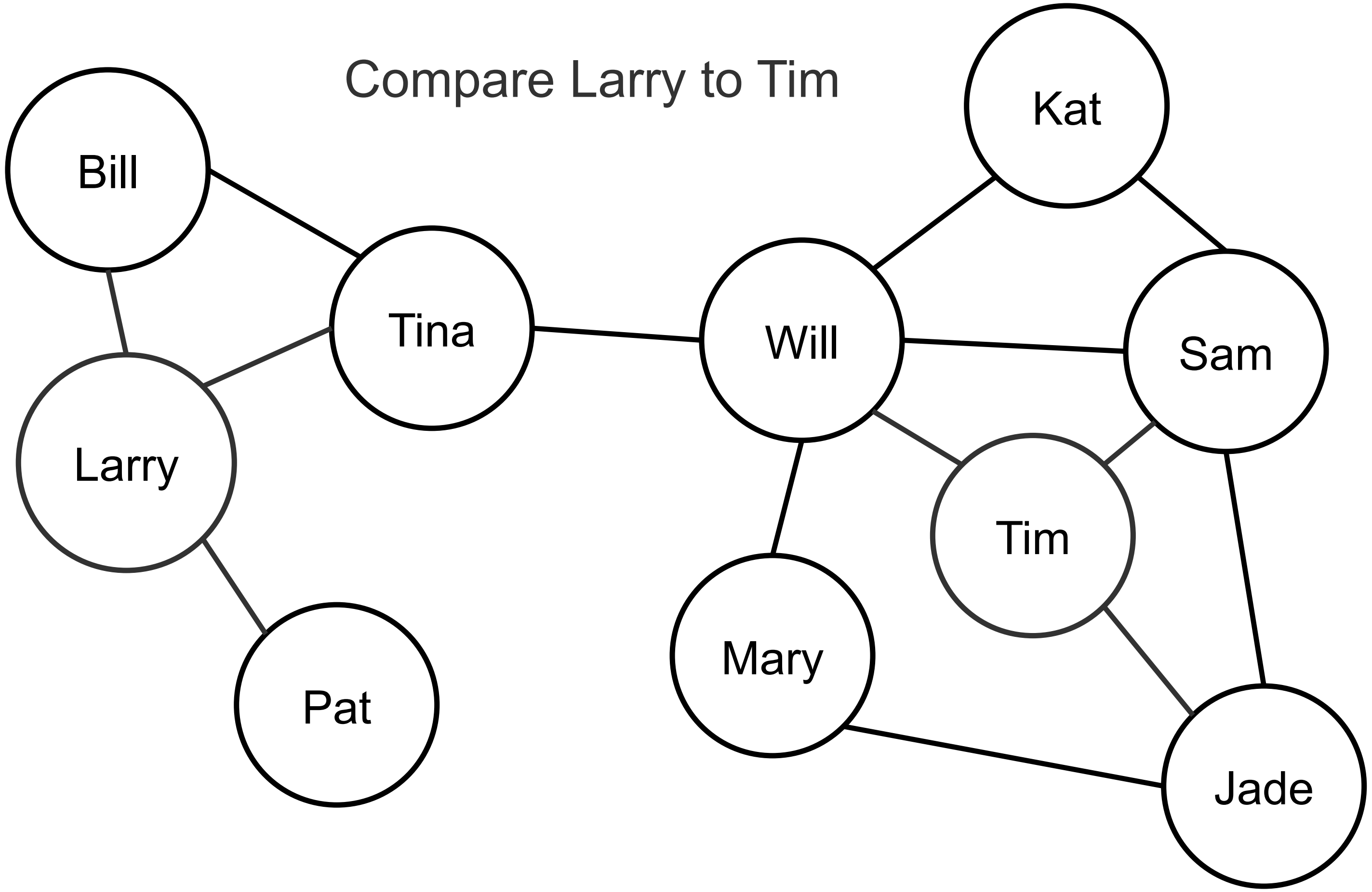
# Location Matters



# Location Matters

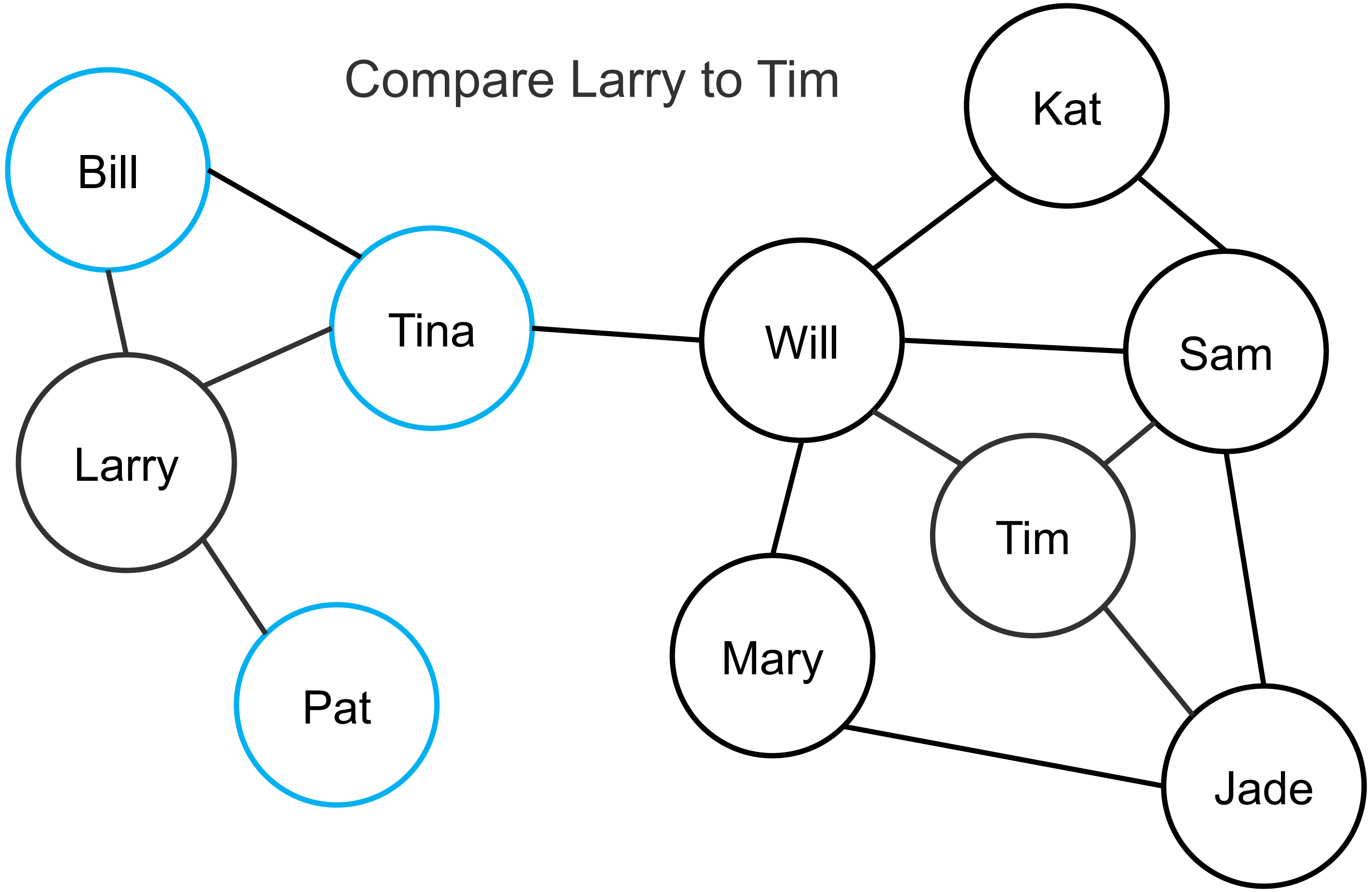


# Location Matters



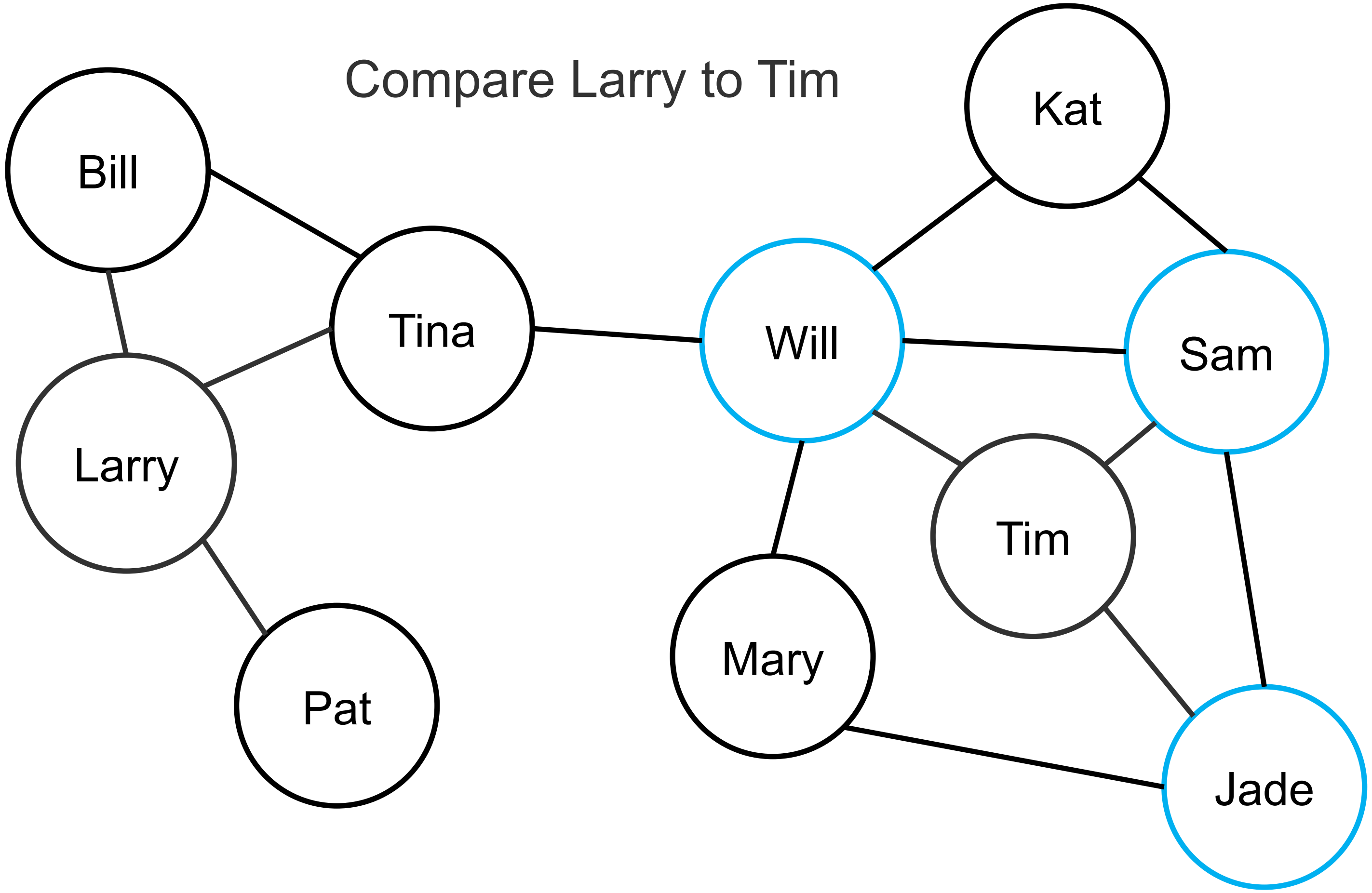
# Location Matters

Compare Larry to Tim



# Location Matters

Compare Larry to Tim



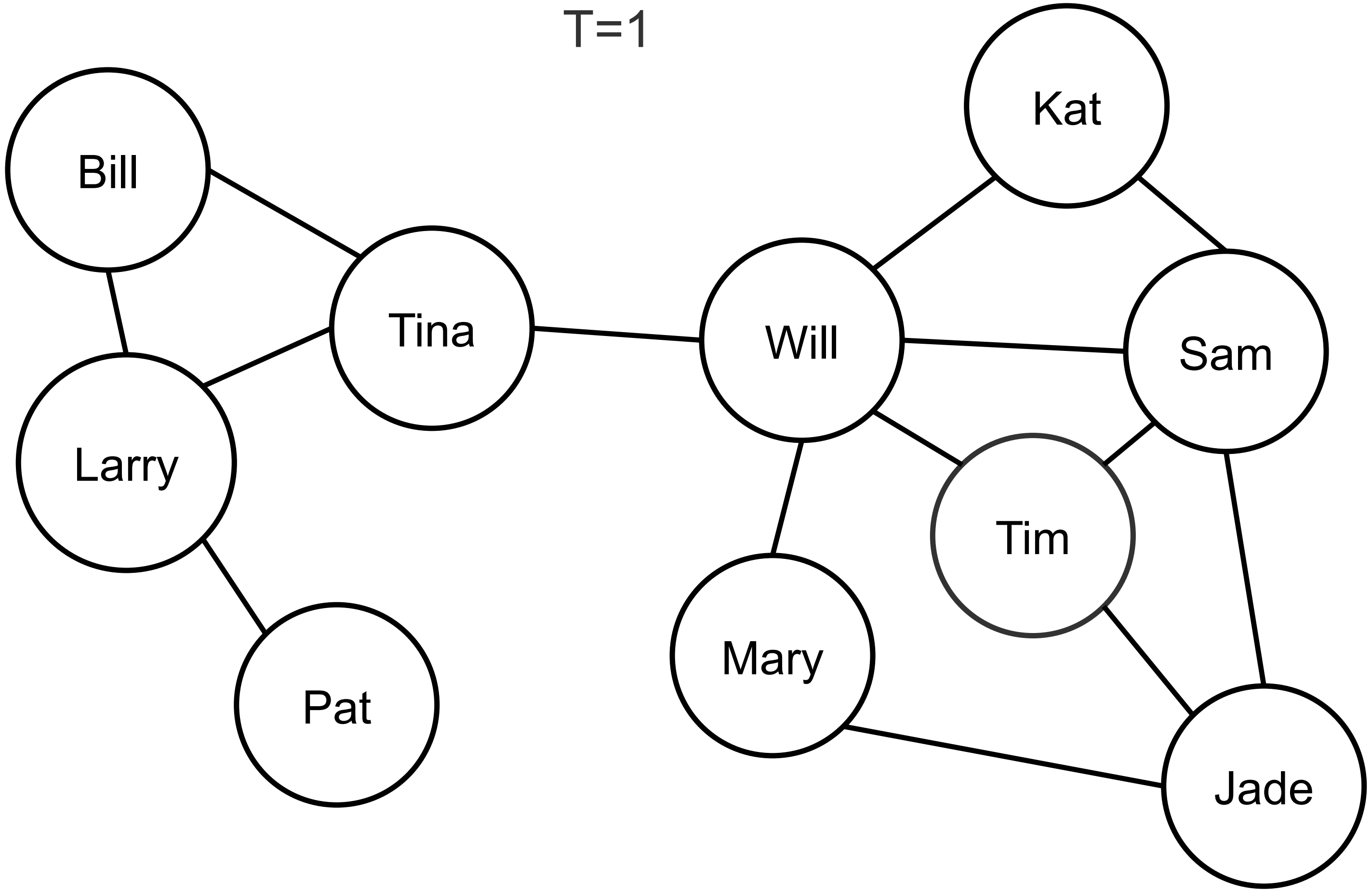
# Location Matters

- Only looking at the counts of the links wouldn't be able to explain the information that is summarized in the graph.
- How is this important?
  - Disease prevention – who would you rather get sick, Larry or Tim?
  - Marketing choices – who would you rather sell your product to, Larry or Tim?

# Location Matters

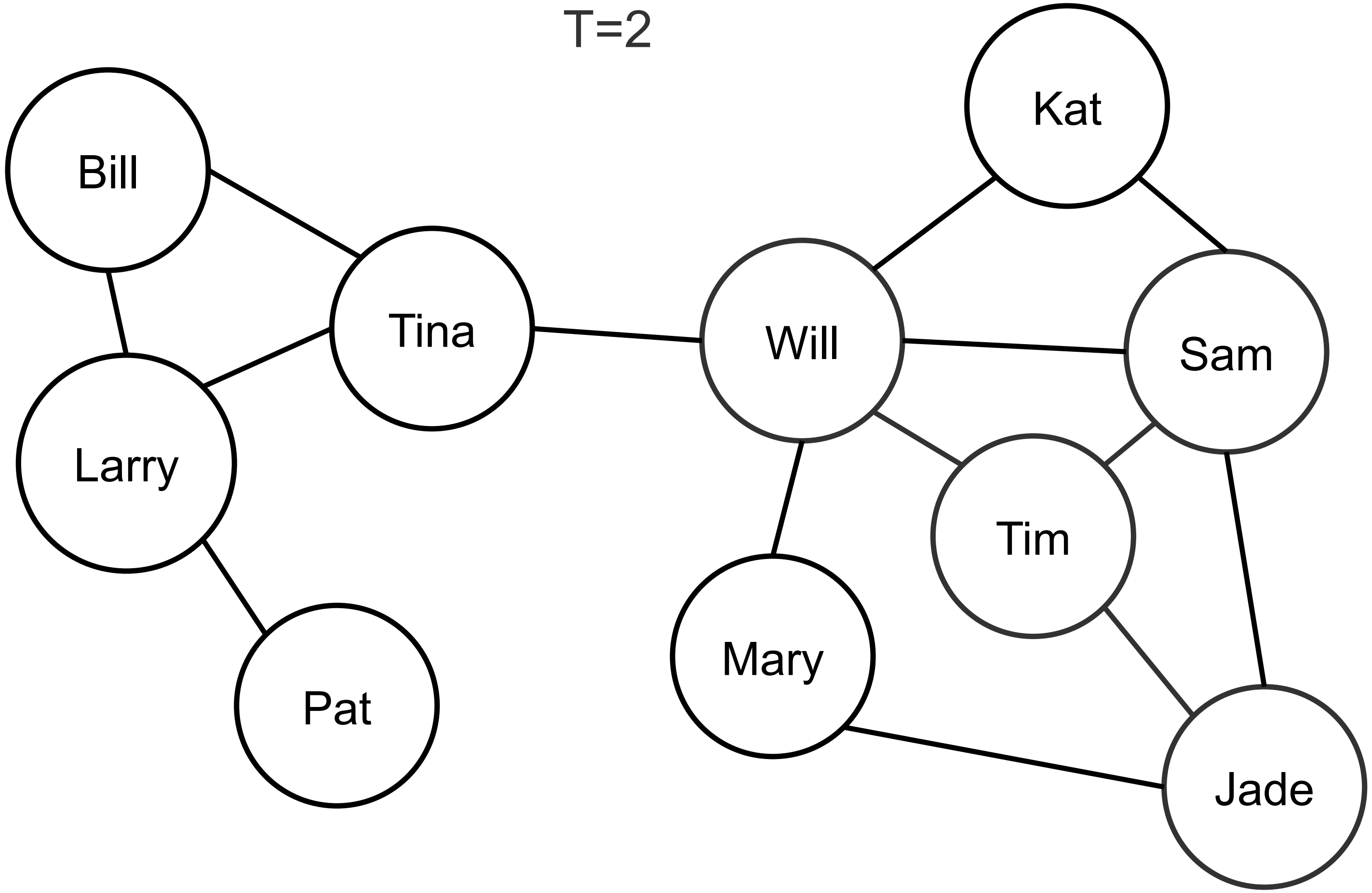
- Let's focus on the disease contamination example.
- Assume the disease moves from one individual to every one of the individual's contacts in one time period.
- This pattern persists in the next time period until all nodes in the network are contaminated.

# Location Matters

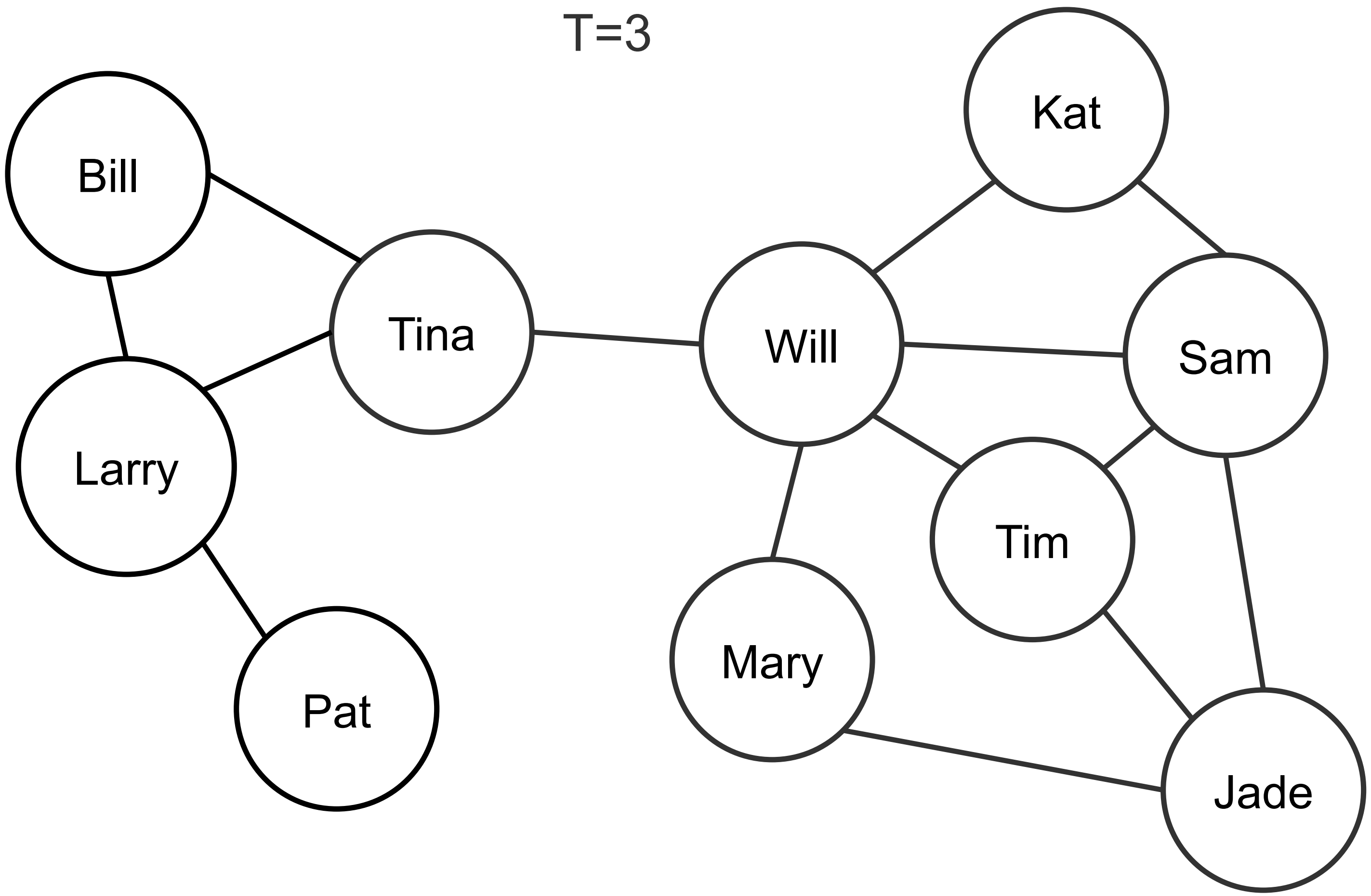


# Location Matters

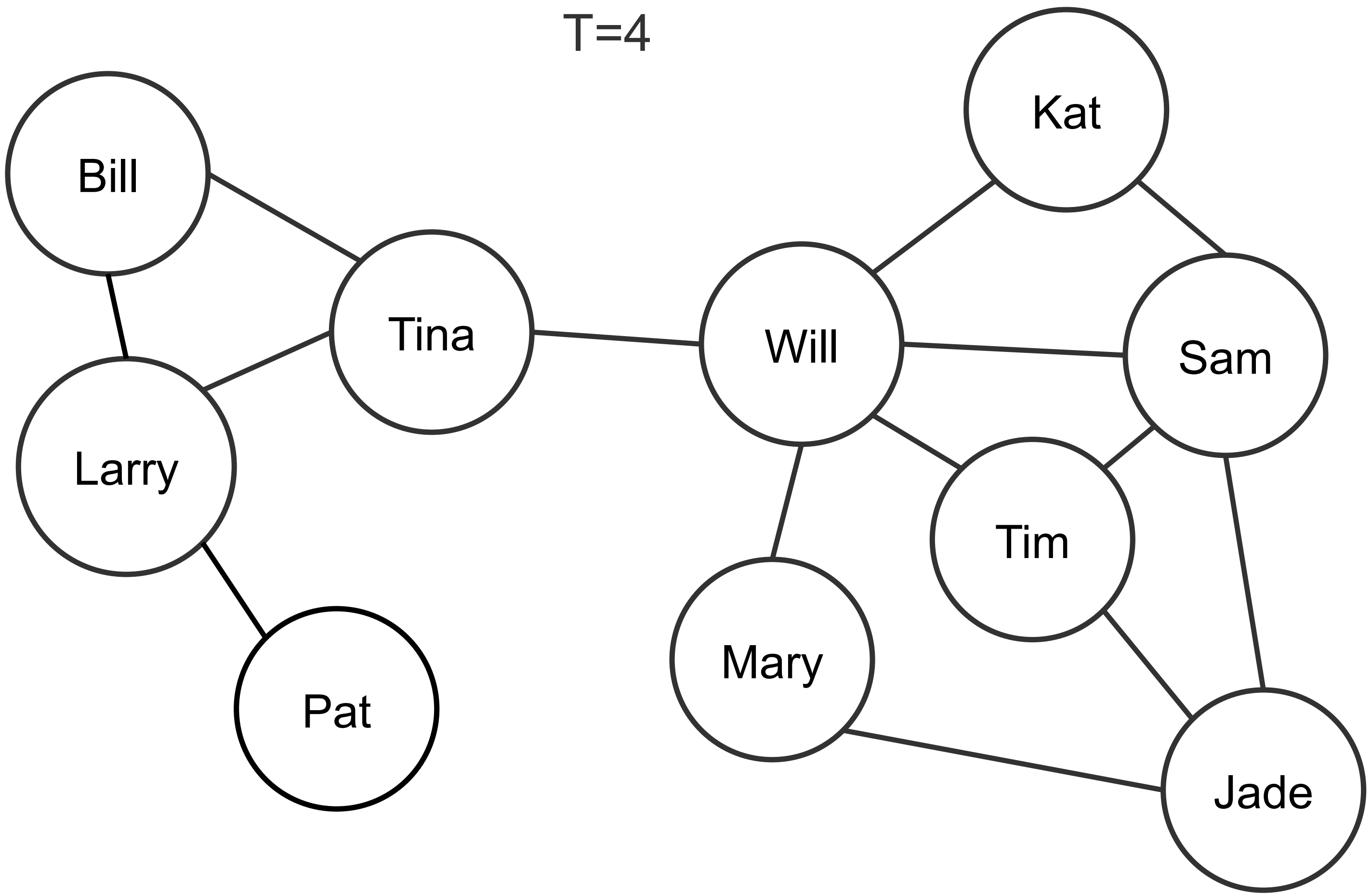
T=2



# Location Matters

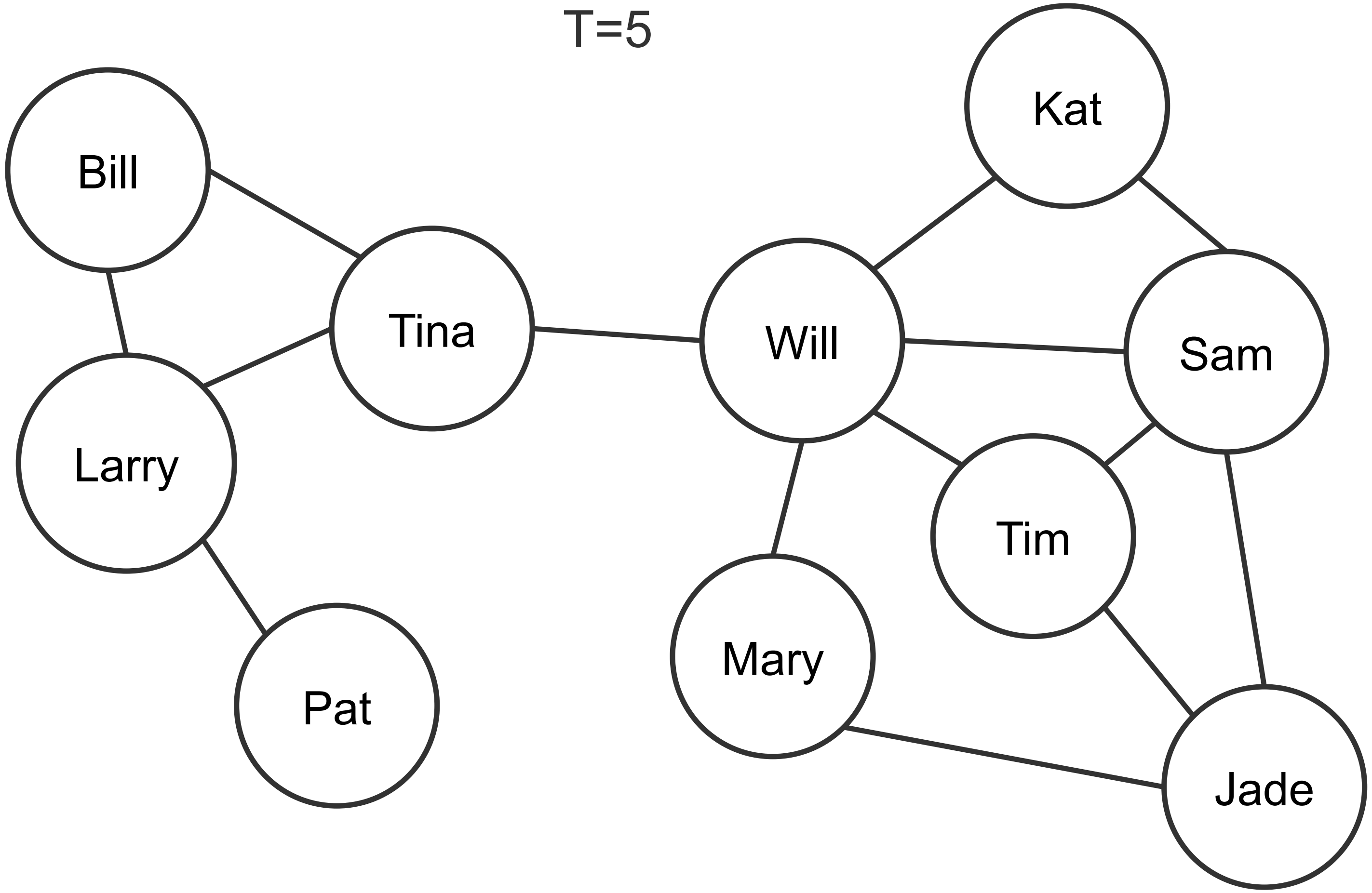


# Location Matters

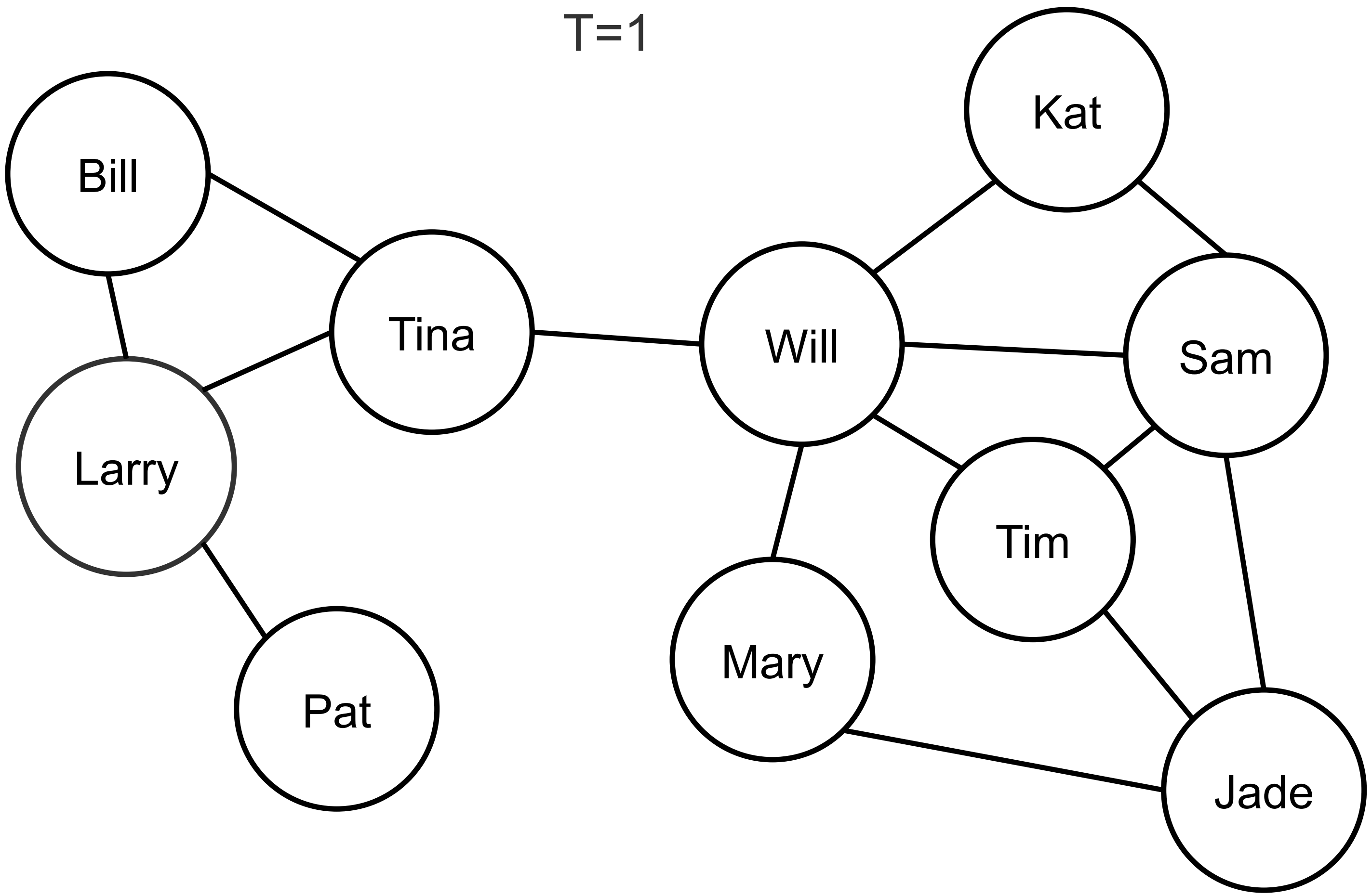


# Location Matters

T=5



# Location Matters



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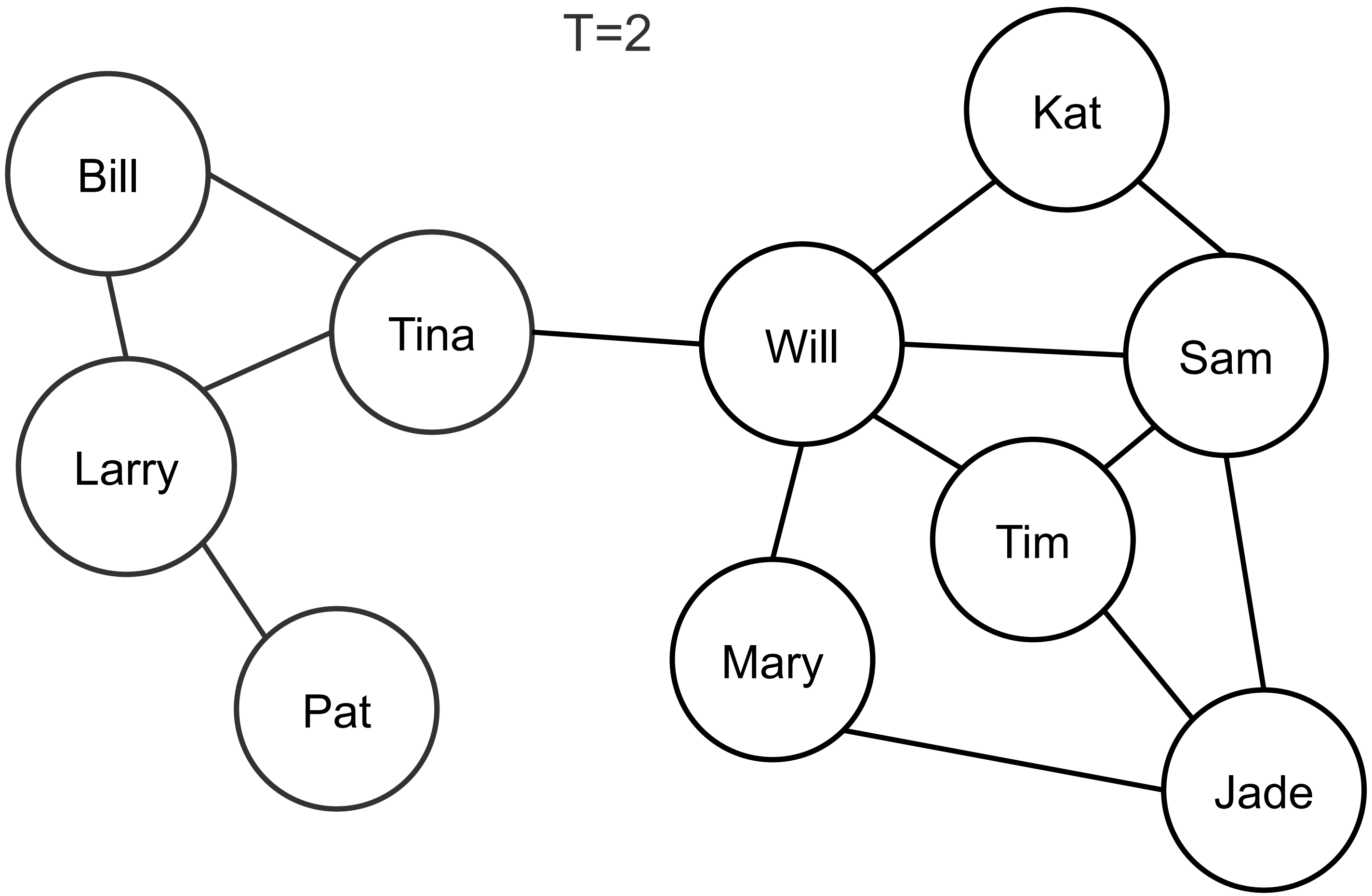

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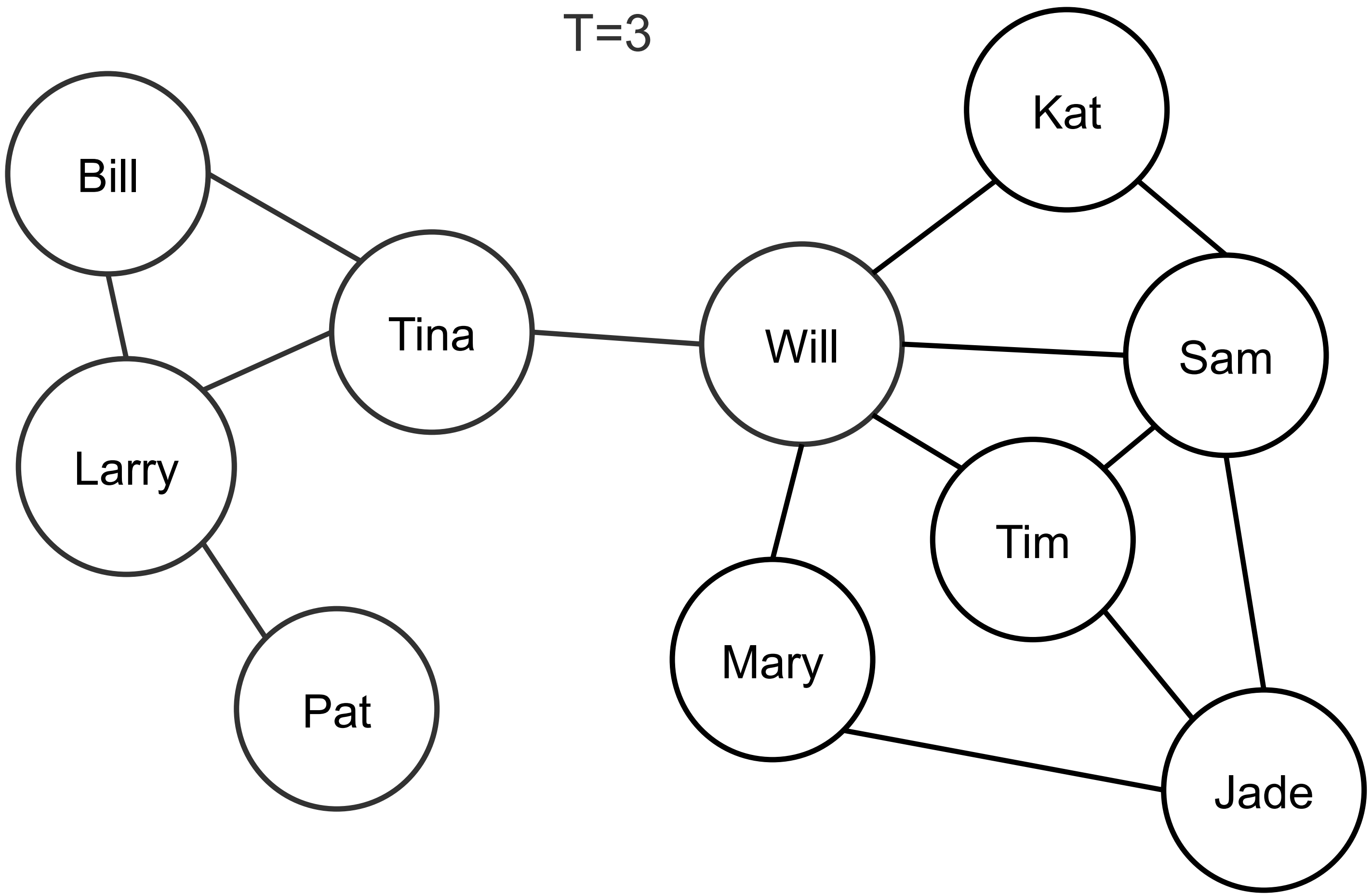

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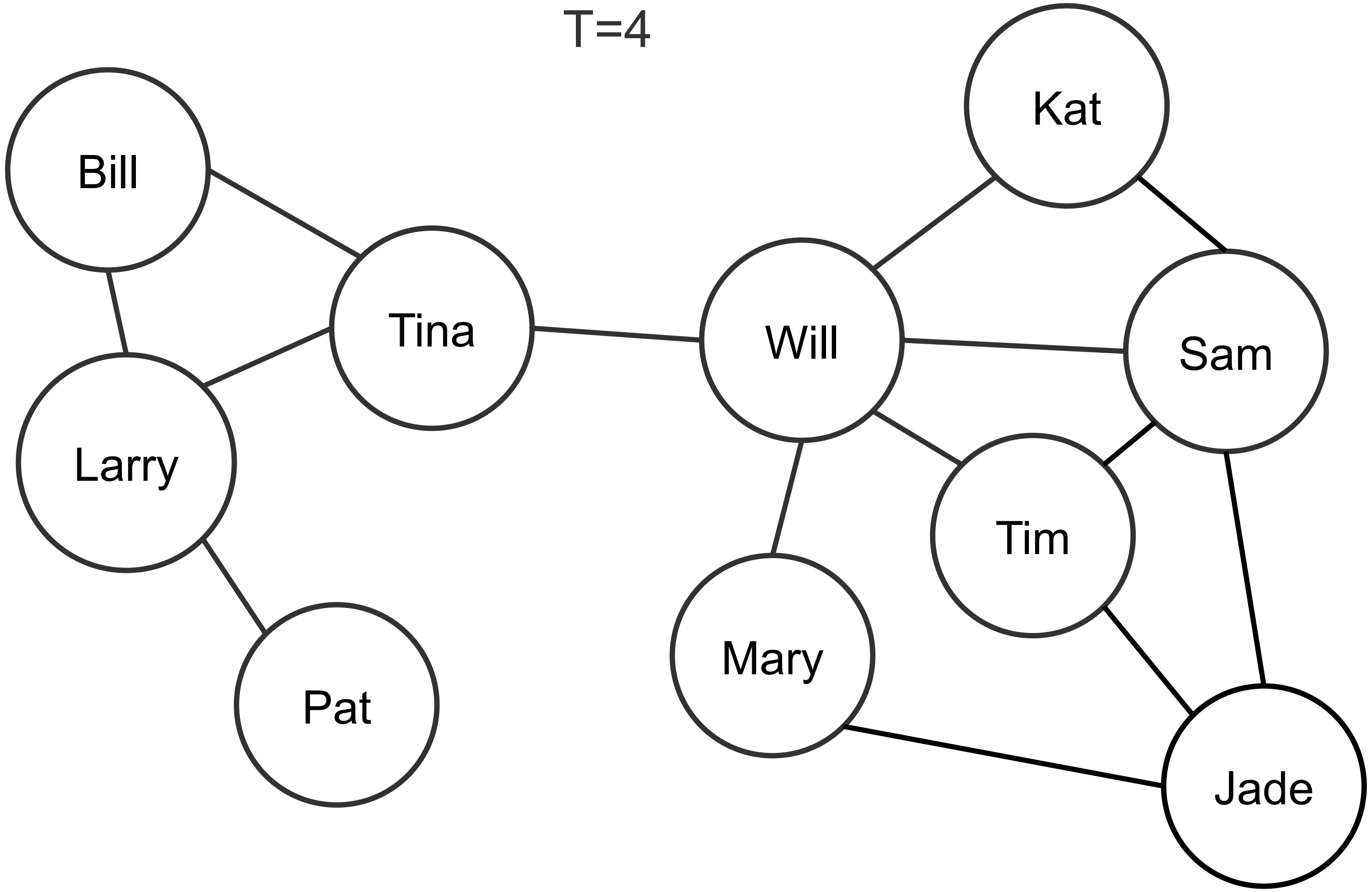

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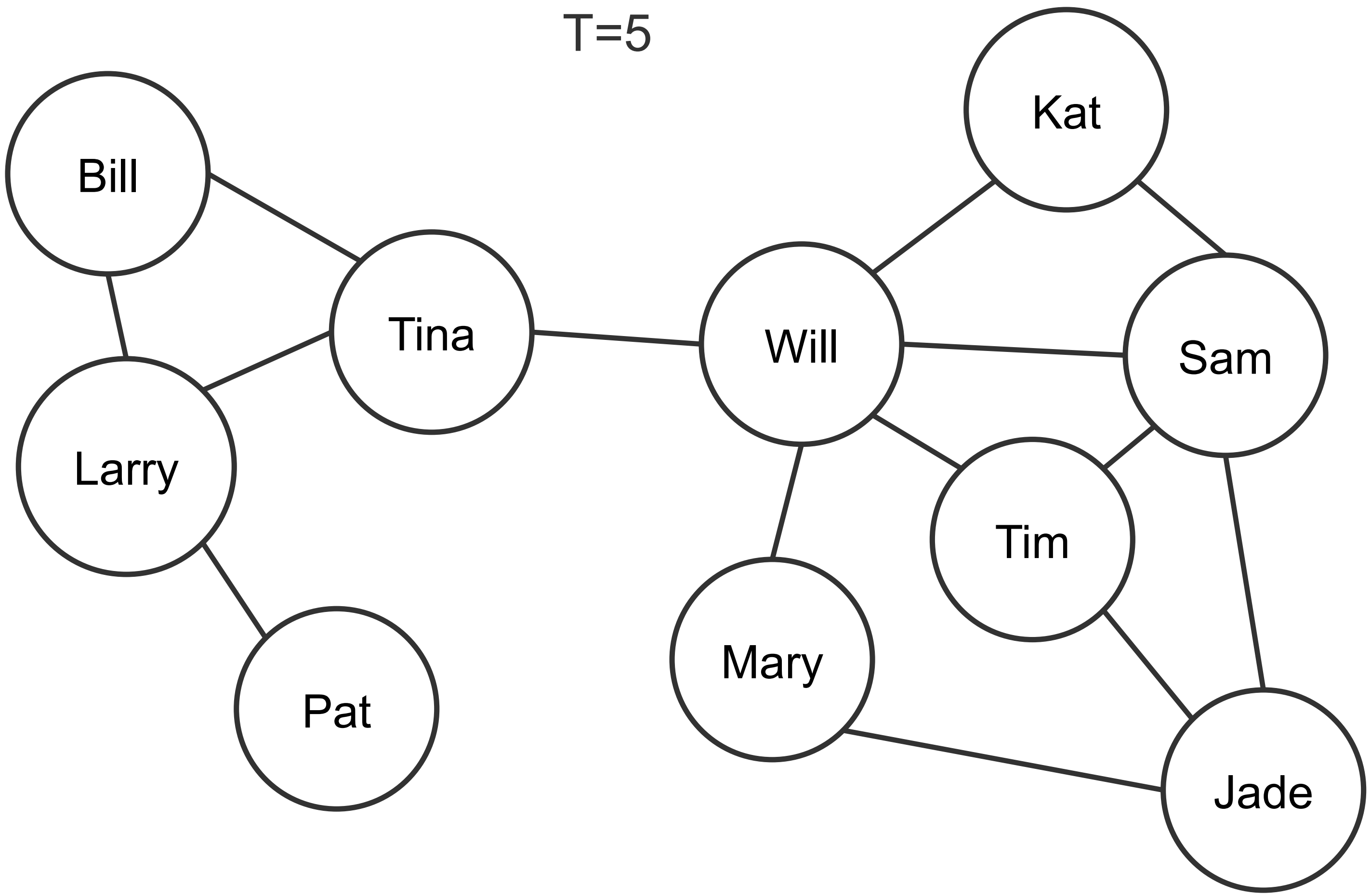

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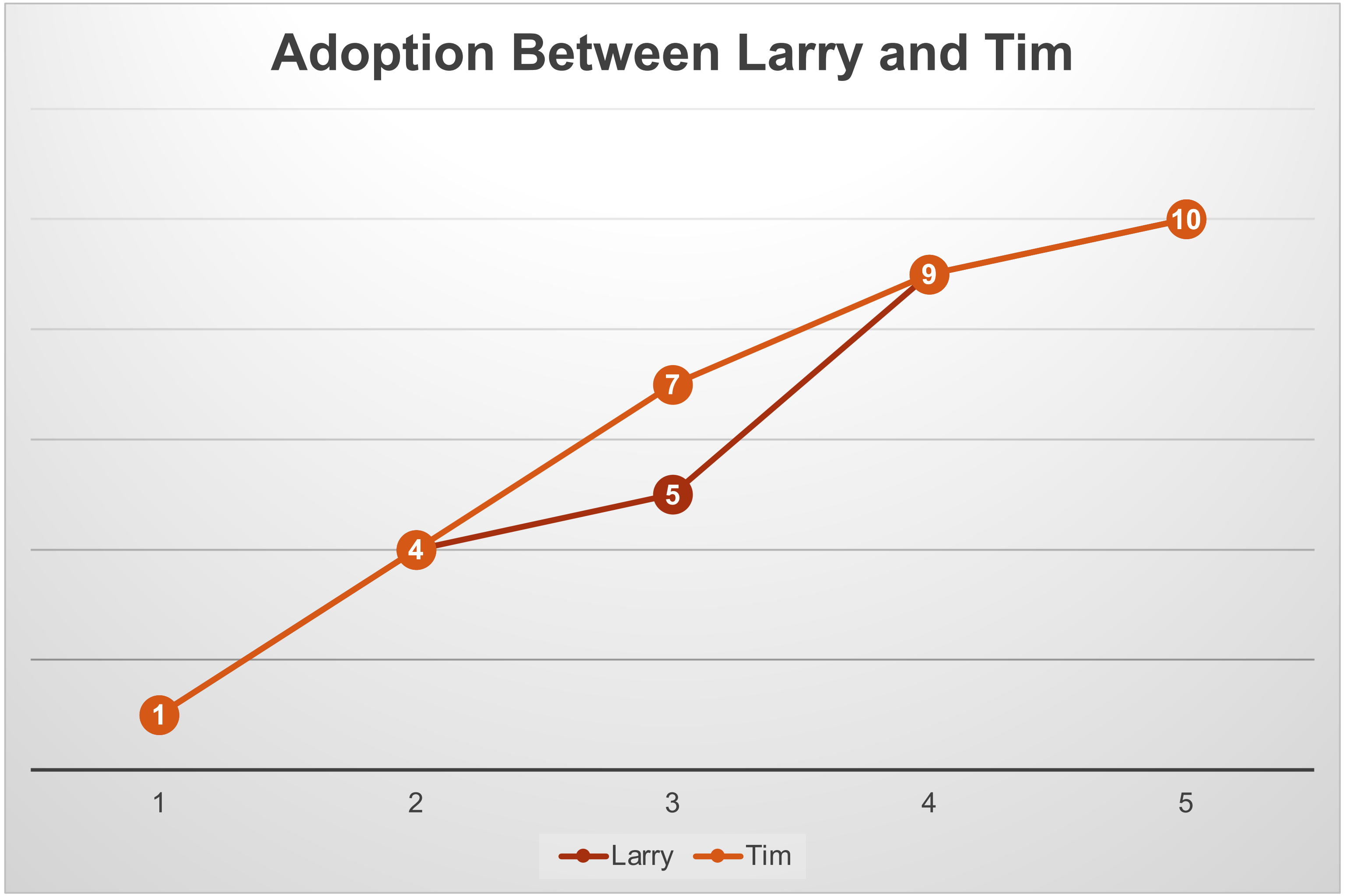

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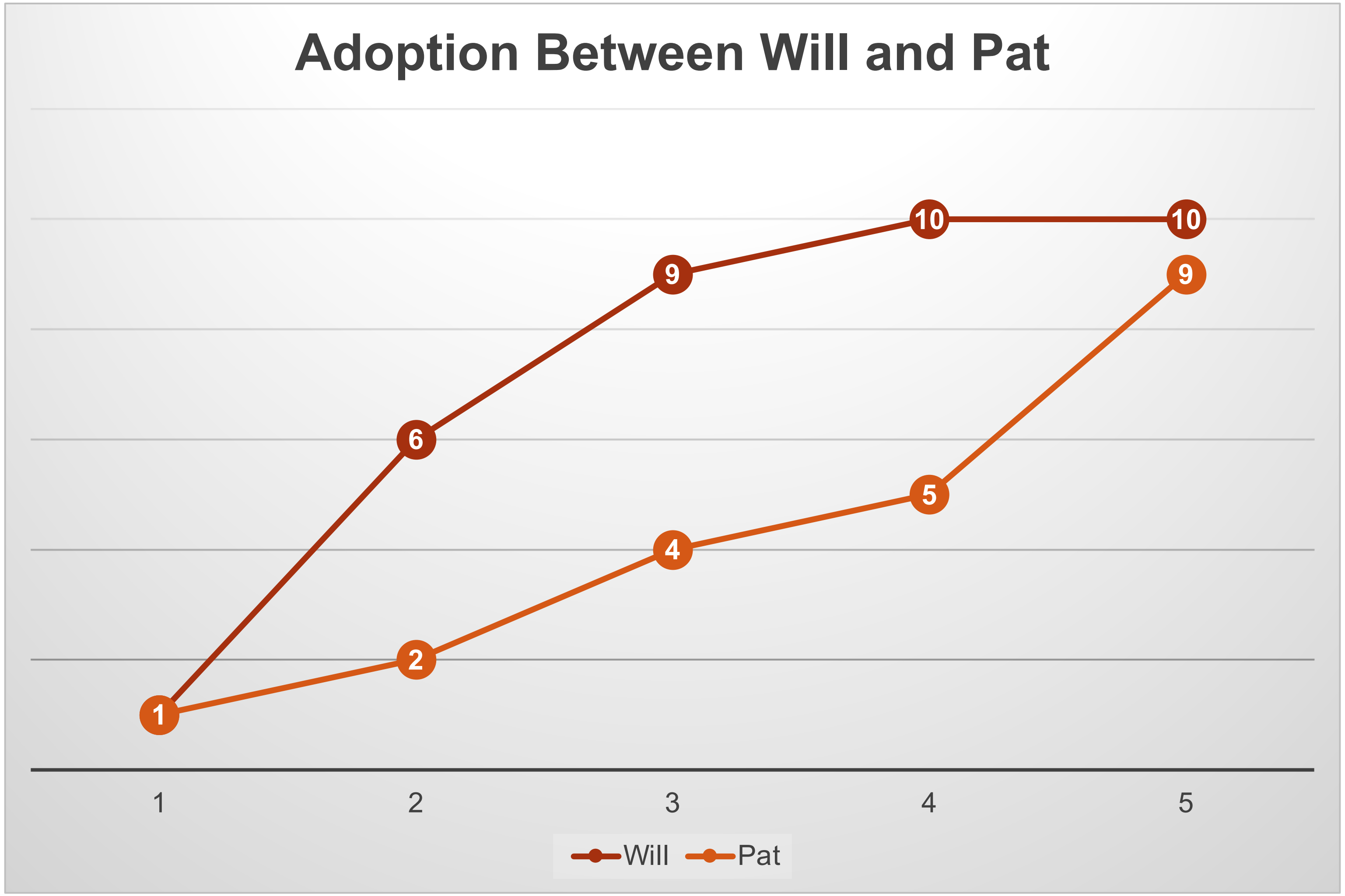
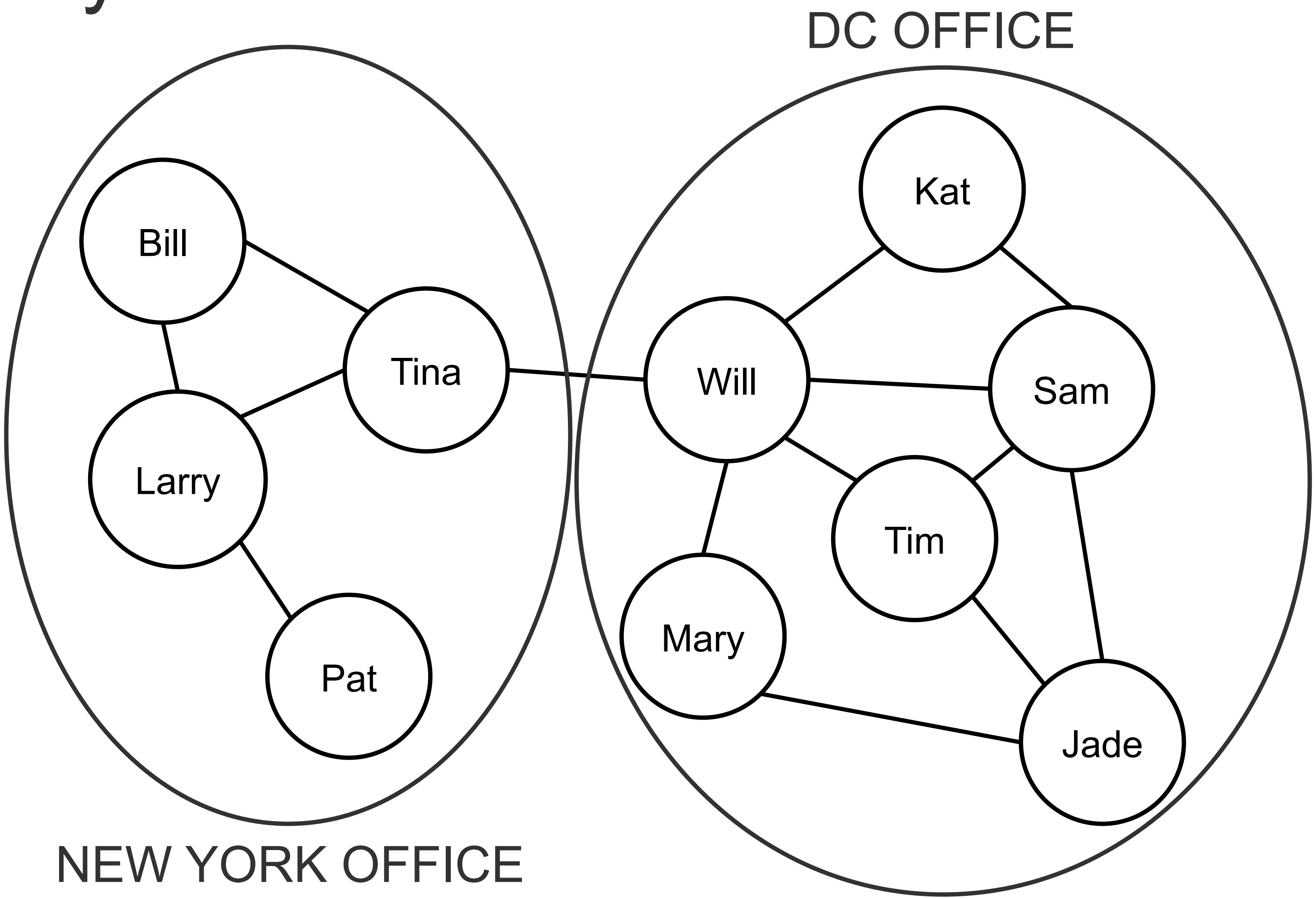


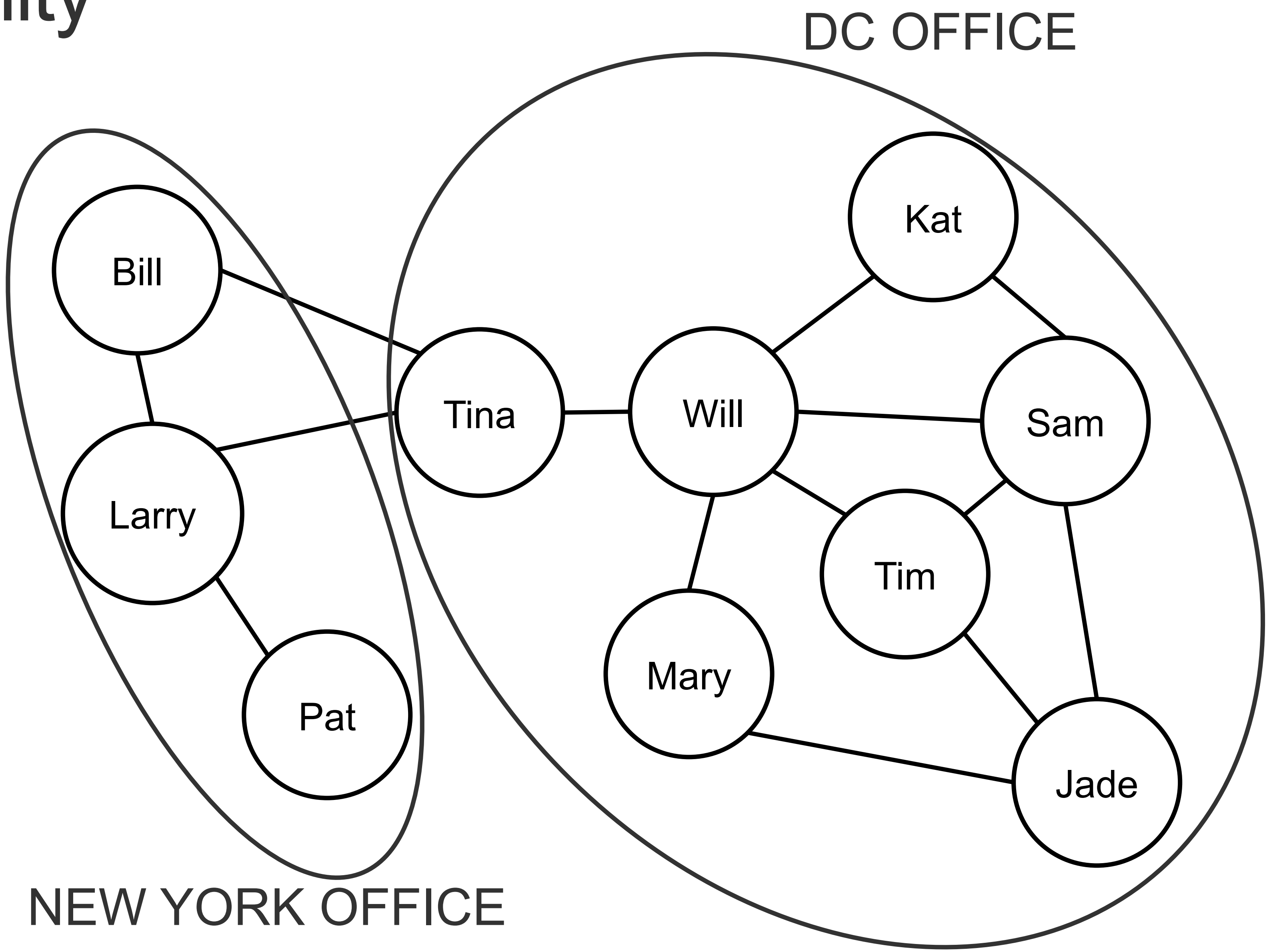
# Diffusion and Adoption

- Diffusion and adoption add a sense of time to a sociogram.
- How long does it take for the entire network to **adopt** an idea based on initial location?
- Three other concepts are heavily related to diffusion and adoption:
  1. Proximity
  2. Prestige
  3. Social Conformity

# Proximity


DC OFFICE
Bill
Tina
Larry
Pat
Kat
Will
Sam
Tim
Mary
Jade
NEW YORK OFFICE

# Proximity


DC OFFICE
Bill
Kat
Tina
Will
Sam
Larry
Tim
Mary
Pat
Jade
NEW YORK OFFICE

# Prestige & Social Conformity

- Prestige and Social Conformity are closely related.
- Individuals who epitomize social norms and values of a group that are perceived by others to be valuable have **prestige**.
- **Social conformity** allows people to validate their own sense of self-worth in a group.
  - Example: Will is the prototypical DC office type employee, so Jade wants to be like Will.

# ACCOUNTING FOR TIME

OPTIONAL SELF STUDY

# Aggregating Time

- Certain transactions are expected to occur at certain times.
- Anomalies might be detected outside of “normal” hours.
- Dealing with time averages and confidence intervals can be tricky.

# Aggregating Time

- What is the arithmetic average between 1 and 23?

# Aggregating Time

- What is the arithmetic average between 1 and 23? **12!**

# Aggregating Time

- What is the arithmetic average between 1 and 23? **12!**

- What is the arithmetic average between 1:00AM and 11:00PM? **NOON?**

# Aggregating Time

- What is the arithmetic average between 1 and 23? **12!**
- What is the arithmetic average between 1:00AM and 11:00PM? **NOON?**
- What is the **periodic** average between 1:00AM and 11:00PM? **MIDNIGHT!**

# Arithmetic Mean

```
set.seed(12345)
timestamp <- as.POSIXlt("2020-02-03 00:30:00")
              + rnorm(1000, 0, 60*60*4)
head(timestamp)
```

```
## [1] "2020-02-03 02:50:31 EST" "2020-02-03 03:20:16 EST"
## [3] "2020-02-03 00:03:46 EST" "2020-02-02 22:41:09 EST"
## [5] "2020-02-03 02:55:24 EST" "2020-02-02 17:13:41 EST"
```

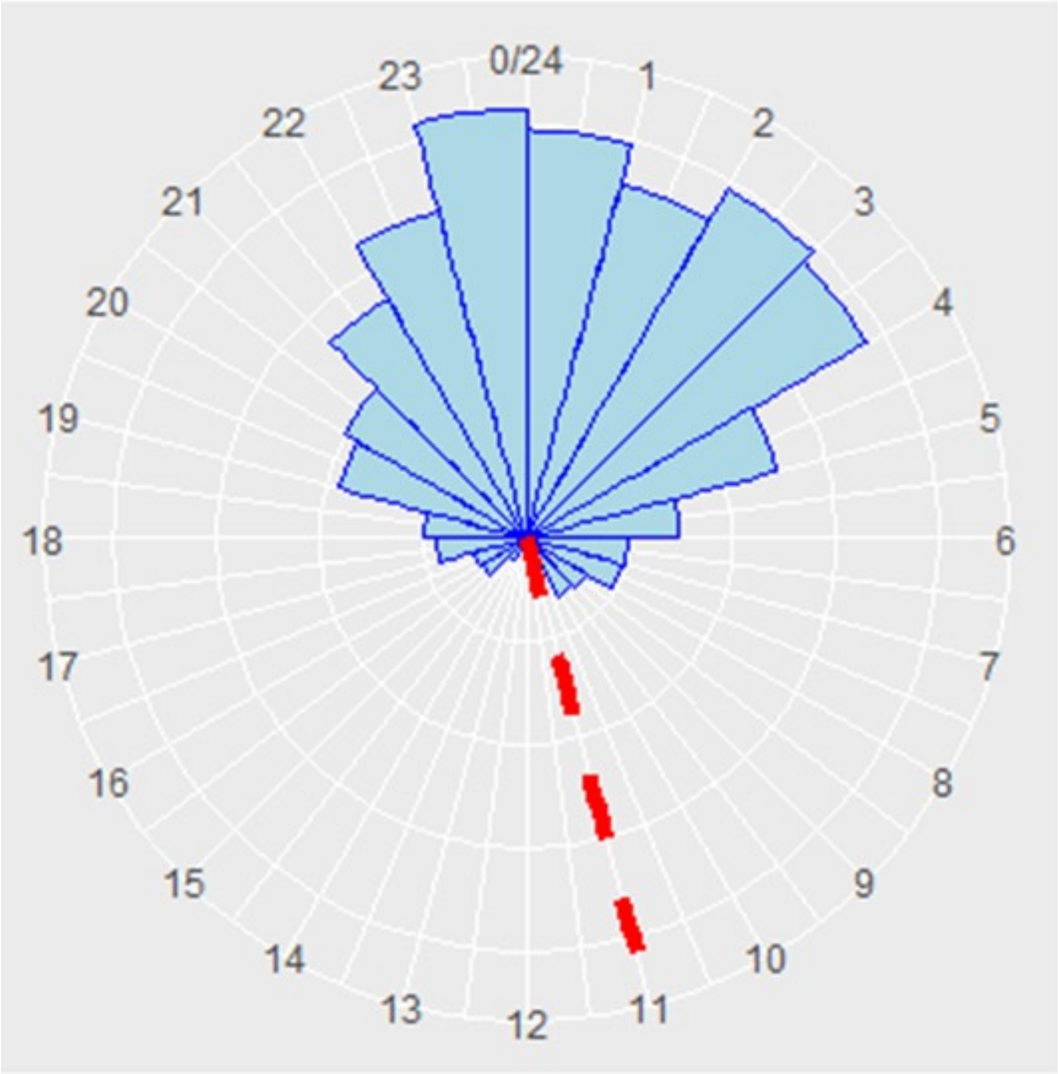
# Arithmetic Mean

```
timestamp_hms <- strftime(timestamp, format = "%H:%M:%S")
ts <- as.numeric(hms(timestamp_hms))/3600
mean_a <- mean(ts)

clock <- ggplot(data.frame(ts), aes(x = ts)) +
         geom_histogram(breaks = seq(0, 24), colour = "blue",
                        fill = "lightblue") +
         coord_polar() +
         scale_x_continuous("", limits = c(0, 24),
                            breaks = seq(0, 24))

clock + geom_vline(xintercept = mean_a,
                   linetype = 2, color = "red", size = 2)
```

# Arithmetic Mean



# Periodic Mean

```
ts <- circular(ts, units = "hours", template = "clock24")
head(ts)
```

```
## Circular Data:
## Type = angles
## Units = hours
## Template = clock24
## Modulo = asis
## Zero = 1.570796
## Rotation = clock
## [1]  2.84194444  3.33777778  0.06277778 22.68583333  2.923333
33 17.22805556
```

# Periodic Mean

```
estimates <- mle.vonmises(ts)
mean_p <- estimates$mu %% 24
concentration <- estimates$kappa

clock + geom_vline(xintercept = mean_p,
                   linetype = 2, color = "red", size = 2)
```

# Periodic Mean