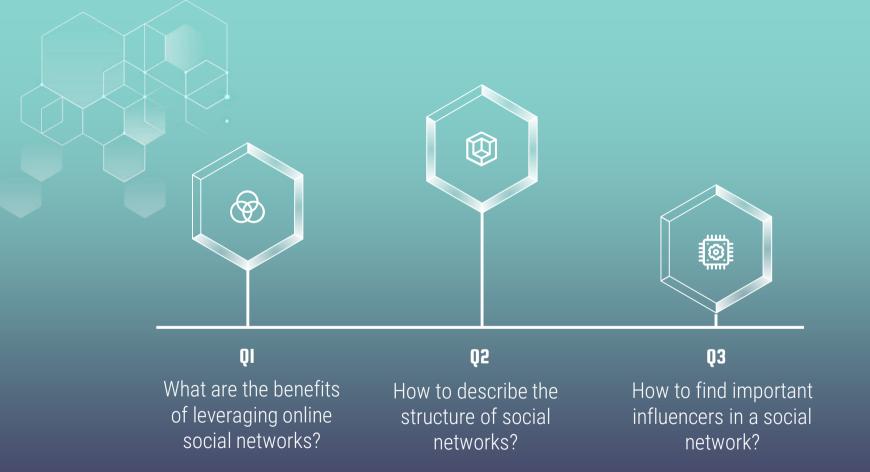
# Social Networks

Connecting with others



## What is the difference?

#### Web 1.0

Expedia
Google
eBay
Amazon.com
CNN.com
WSJ.com

### Web 2.0 and beyond

Twitter
Snapchat
Instagram
Pinterest
Reddit
Wikipedia
Facebook



### **Get Fans**



The vast majority of large brands today have an active social media presence, such as FB fan page. For brands to resonate on Facebook, the first step is to accumulate your fan base.

## Engage



Brand messages only reach subset of fans.

Users that engage in fan page more likely to receive messages on news feed.

Users can engage by liking, sharing, posting, commenting and checking in.



## **Amplify**



Spread brand message across social network (i.e., newsfeed).

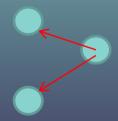
Organic word-of-mouth advertising.

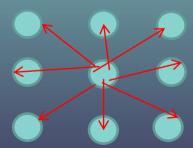
Network can also be used for social advertising.

## **Amplification Ratio**

Amplification ratio

= # Friends of Fans exposed / # Fans exposed

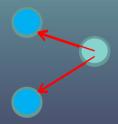


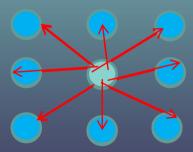


## **Amplification Ratio**

### Amplification ratio

= # Friends of Fans exposed / # Fans exposed

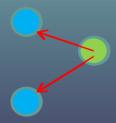


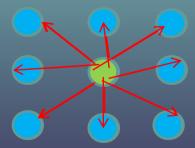


## **Amplification Ratio**

### Amplification ratio

- = # Friends of Fans exposed / # Fans exposed
- = 10/2 = 5.





### **AMPLIFICATION RATIO**

Here are some facts. According to FB:

The top ten corporate brands had an average Amplification Ratio average of 1.05 (Range: 0.42 to 2.18).

The top 100 brands (excluding Celebrities & Entertainment) had an average Amplification Ratio of 0.84 (Range: 0.06 to 2.87).

## **CASE STUDY: Holiday Sales**

Case study focused on Amazon, Best Buy, Target and Walmart.

Retailers offered Facebook fans Black Friday deals.

Friends of Fans received notifications about their friends becoming fans, which lead to increased amplification.

Online and offline purchases of exposed fans and Friends of Fans compared to typical week.

## **CASE STUDY: Holiday Sales**

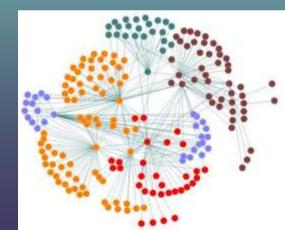




## Social Network Analysis Useful for...

Spotting influential people
Who has a lot of linkages?
Who is vital at linking people up?
Why not just looking at no. of friends/followers?
Strength of tie

Understanding how connected the network is How many people are connected?
What is the longest path between people?
How to measure the density of a network?



## **Metrics**

#### Individual

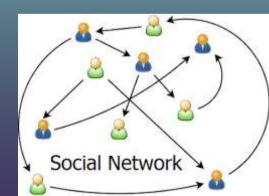
Has meaning independently of social network You live in Hong Kong island, HK

#### Connection

You are close friends with 10 people at HKU

#### Whole Network

On average, students know each other within 4 steps





## Edges

Person 1





## **Edges**

Person 1

Person 2





Undirected (e.g., study at HKU)

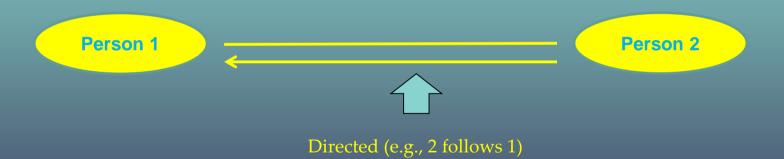


Person 1

Person 2



## **Edges**



## **Edges**

Person 1 Person 2

Edges are also called links or ties.

## **Nodes and Edges**

Vertex/Node: an end point Often a person

Edge/Link: What connects up the Nodes A relationship

Maximum number of edges in group of size N(N-1)/2. Where everyone connects to everyone else If undirected (my friends also have me as a friend)

### Who is well-connected?

Degree (centrality): The number of linkages you have.

"In-degree", e.g., someone that follows me.

"Out-degree", e.g., I follow someone else.

#### Edge Weight

Sometimes edge can also carry weight
Can capture how deep the relationships are
E.g., frequency of interactions between two nodes.



## QUESTION

How to determine the influential person (i.e., node) in a social network?



## QUESTION

How to define the importance of a node?

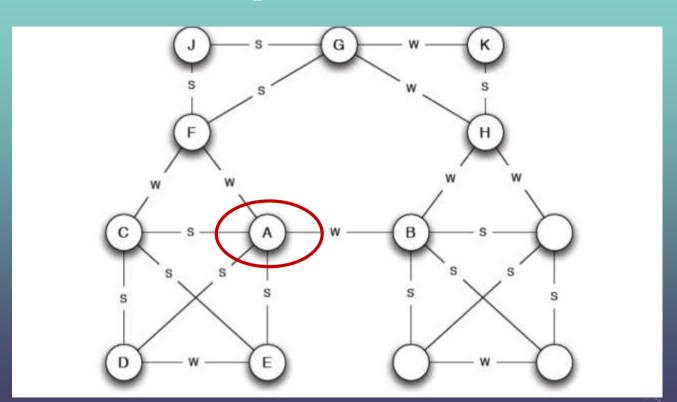


## Strong vs. Weak Ties

Suppose that two individuals are connected in a social network (i.e., they know each other).

However, the strength of their connection may differ: It may be a strong tie (i.e., they are friends) or a weak tie (they are acquaintances).

## Strong vs. Weak Ties

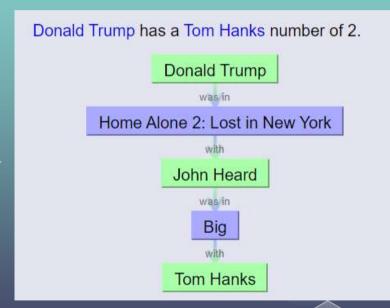


## **Degrees of Separation**

Path of how many people are needed to connect people up
Technical name: Geodesic distance

6 is the magical number: Kevin Bacon game (Link)

Don't fixate on 6! It does not apply to all networks!



## Is a Network Well-Connected?

Graph/network density

### **Network Density**

Potential Connections:

$$PC = \frac{n \cdot (n-1)}{2}$$

Network Density: Actual Connections Potential Connections

#### Examples:



Nodes (n): 2 Potential Connections: 1 (2\*1/2) Actual Connections: 1

Network Density: 100% (1/1)



Nodes (n): 3 Potential Connections: 3 (3\*2/2)

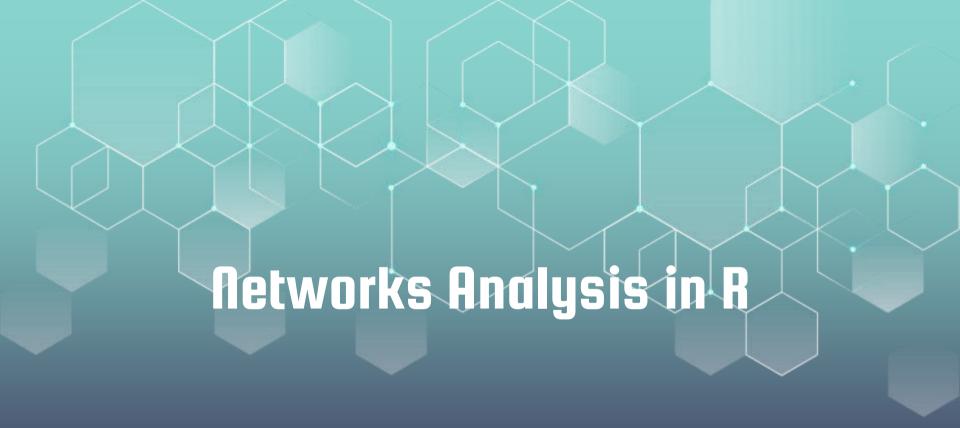
Actual Connections: 3 Network Density: 100% (3/3



Nodes (n): 3 Potential Connections; 3 (3\*2/2) Actual Connections; 2

Actual Connections: 2 Network Density: 66.7%

(2/3)



## **Preparing Packages**

library(igraph) library(readr)

The "igragh" package provides you tools for network analysis while the "readr" facilitates reading data.

## **Reading Data**

```
actors <-
read_csv("https://ximarketing.github.io/class/D
M//Actors.csv")
movies <-
read_csv("https://ximarketing.github.io/class/D
M/Movies.csv")</pre>
```

Here, the first file contains the nodes information, whereas the second file contains the edge information. Each actor/actress is a node, and if two actors/actresses appear in a same movie, there is an edge between them.

## **Reading Data**

#### Actor Information (nodes):

```
> head(actors)
# A tibble: 6 x 3
 Actor
             Gender BestActorActress
 <chr>>
             <chr>
                     <chr>>
 Tom Hanks Male
                     Winner
 Gary Sinise Male
                     None
3 Robin Wright Female None
4 Bill Paxton Male
                     None
 Kevin Bacon
              Male
                     None
6 Ed Harris
              Male
                     Nominated
```

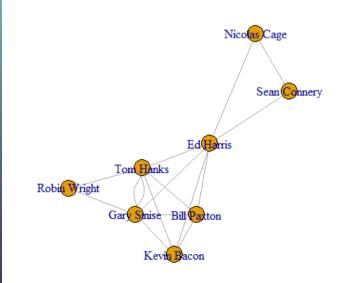
## **Reading Data**

#### Movie Information (edges):

```
> head(movies)
# A tibble: 6 x 3
 'Actor 1' 'Actor 2' Movie
 <chr> <chr>
                        <chr>
1 Tom Hanks Gary Sinise Forest Gump
2 Tom Hanks Robin Wright Forest Gump
 Gary Sinise Robin Wright Forest Gump
 Tom Hanks
            Gary Sinise
                        Apollo 13
5 Tom Hanks
            Bill Paxton
                        Apollo 13
6 Tom Hanks Kevin Bacon Apollo 13
```

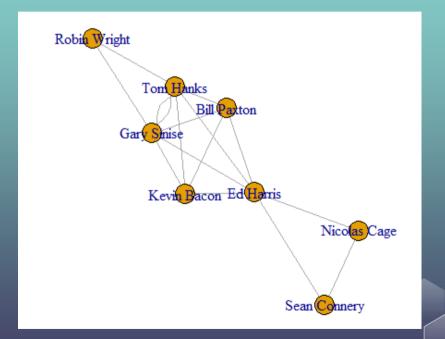
### Visualize the Network

```
actorNetwork <-
graph_from_data_frame(d=movies,
vertices=actors, directed=F)
plot(actorNetwork)</pre>
```



### Visualize the Network

plot(actorNetwork)

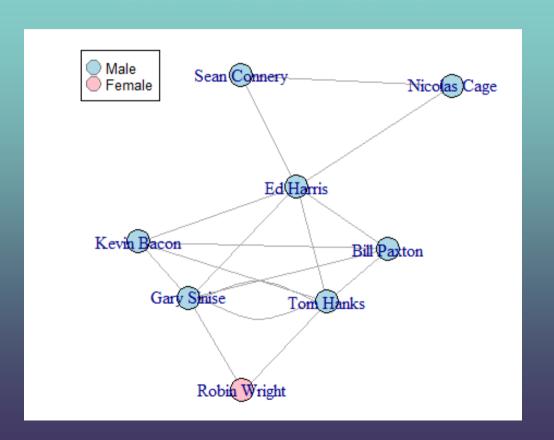


#### Visualize the Network

You can also add colors to your nodes:

```
V(actorNetwork)$color <-
ifelse(V(actorNetwork)$Gender == "Male",
"lightblue", "pink")
plot(actorNetwork)
legend("topleft", c("Male", "Female"),
pch=21,
  col="#777777",
pt.bg=c("lightblue","pink"), pt.cex=2,
cex=.8)
```

### Visualize the Network



### Degree of the nodes

To check the degree of nodes in the network:

degree(actorNetwork, mode="all")

```
Tom Hanks Gary Sinise Robin Wright Bill Paxton Kevin Bacon Ed Harris
6 6 2 4 4 6
Sean Connery Nicolas Cage
2 2
```

### **Closeness/Betweenness Centrality**

```
closeness(actorNetwork, mode="all",
weights=NA, normalized=T)
```

```
Tom Hanks Gary Sinise Robin Wright Bill Paxton Kevin Bacon Ed Harris
0.7777778 0.7777778 0.5000000 0.7000000 0.7000000 0.8750000
Sean Connery Nicolas Cage
0.5384615 0.5384615
```

betweenness(actorNetwork, directed=F,
weights=NA, normalized = T)

```
Tom Hanks Gary Sinise Robin Wright Bill Paxton Kevin Bacon Ed Harris
0.1190476 0.1190476 0.0000000 0.0000000 0.0000000 0.4761905
Sean Connery Nicolas Cage
0.0000000 0.0000000
```

## **Network Density**

edge\_density(actorNetwork)

#### **Exercise**

There are another two files containing social networks of movie actors and actress. Play with these files yourselves! The files are downloadable here:

```
actors <-
read_csv("https://ximarketing.github.io/class/DM//Ac
torsExercise.csv")
movies <-
read_csv("https://ximarketing.github.io/class/DM/Mov
iesExercise.csv")</pre>
```

#### **Directed Network**

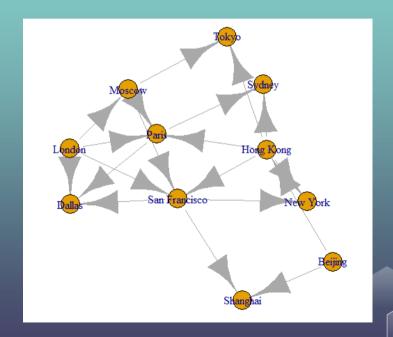
In the following exercise, we play with directed network. This is not much difference.

```
cities <-
read_csv("https://ximarketing.github.io/class/DM/Dir
ectedNodes.csv")
routes <-
read_csv("https://ximarketing.github.io/class/DM/Dir
ectedEdges.csv")
flightNetwork <- graph_from_data_frame(d=routes,
vertices=cities, directed=T)</pre>
```

### **Directed Network**

Plot the directed network:

plot(flightNetwork)



#### **Directed Network**

We can distinguish between in-degrees and out-degrees:

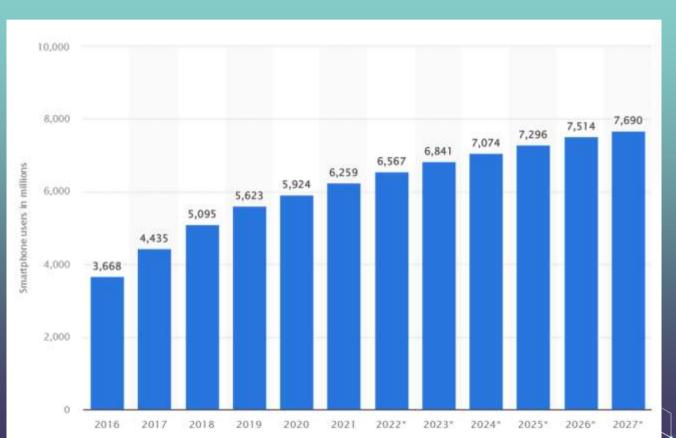
degree(flightNetwork, mode="in")

Beijing 0 Sydney 2	Shanghai 2 San Francisco 3	Hong Kong 1 Paris 4	Tokyo 2 Moscow 1	New York 2 Dallas 3	London 0
	degree <b>(</b> fli	ghtNetwork,	mode="out	.")	

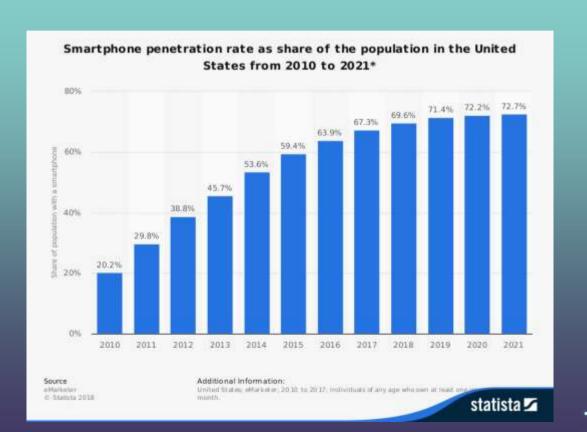
Beijing	Shanghai	Hong Kong	Tokyo	New York	London
2	0	5	0	0	5
Sydney Sai	n Francisco	Paris	Moscow	Dallas	
0	3	2	3	0	



### The Rise of Mobile



### The Rise of Mobile





Which APPs are most downloaded?





Which APPs do people spend most money on?



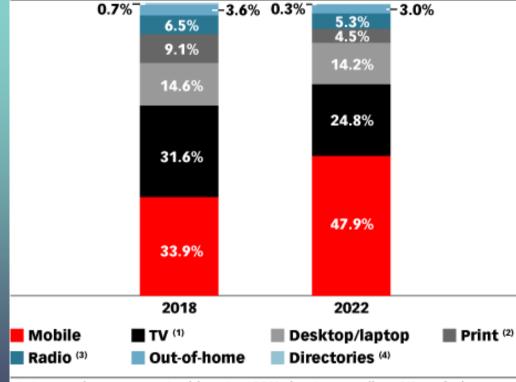


How many hours do people spend on smartphones everyday?





% of total



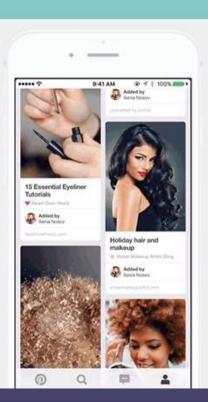
Note: numbers may not add up to 100% due to rounding; (1) excludes digital; (2) includes newspapers and magazines; excludes digital; (3) excludes off-air radio and digital; (4) print only; excludes digital Source: eMarketer, March 2018

235956

www.eMarketer.com

## **Motion Based Ads (on Pinterest)**







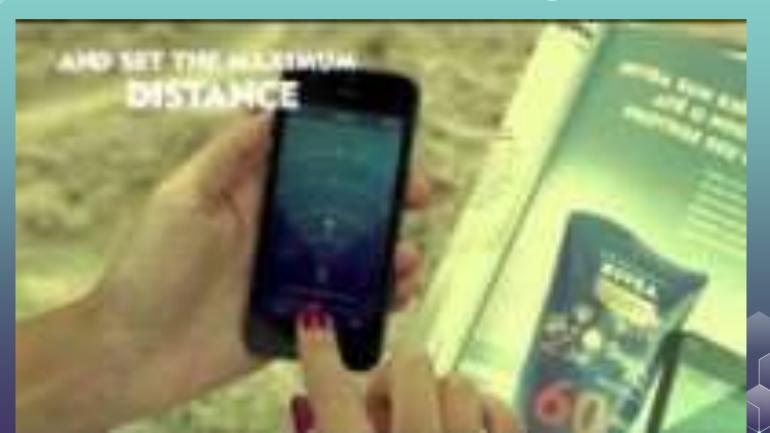
How is mobile different from PC? What new marketing opportunities are brought by mobile?



## Mobile is not just your phone



## A smart use of beacons by Nivea





How are Geo-fencing and Beacons different from traditional outdoor and in-store ads?