# Social Contagion

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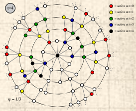
## Principles of Complex Systems, Vols. 1, 2, & 3D
## CSYS/MATH 300, 303, & 394, 2022–2023 | @pocsvox

Prof. Peter Sheridan Dodds | @peterdodds

Computational Story Lab | Vermont Complex Systems Center
Santa Fe Institute | University of Vermont

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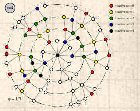

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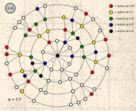
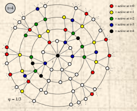


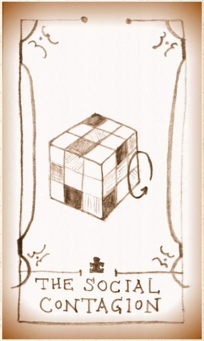
# Outline



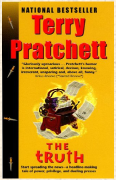




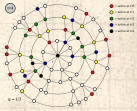

THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
WELL OF SCALES
THE LAWS OF DECAYING POWER
THE UNEXPECTED TRANSFIGURATION
MINISTRY OF RANDOM WALKS
THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE LAW OF DIGITS FIRST
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE MEASURING
THE DATA POOR
THE POURING DATA
THE CHARMS OF THE MANY WRONG PATHS
THE DOORS THAT SHOULD NOT BE OPENED
THE KNOWLEDGE OF DEAD MONKS
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
THE ARK OF THE RANDOM NETWORK
THE STRANGENESS OF FRIENDS
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
THE CONTAGION
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE THRESHOLDS OF THE MIND
THE SOCIAL WILD
THE RATIO OF GAIN
THE MECHANICS OF FAME
THE TALK OF FAME
THE STORIES CONTAGIOUS
THE JOHN DORY
THE ADJACENT NARRATIVES
THE STORYTELLERS
THE FATED ASTRAL PATH
THE PATHS OF UNIVERSALITY
THE DEPENDENT PATHS
THE TROUSERS OF BIFURCATING REALITIES
THE UNKNOWN MECHANISM
THE LANDSCAPES OF FORKING PATHS
THE NETWORKS OF BLOOD
THE TREES OF REALITY
THE ORDERS OF STREAMS
THE LAWS OF BRANCHING
THE SCALING OF BROKEN HIERARCHIES
THE BRAID OR THE BRANCH
THE LAW OF OPTIMAL FORKS
THE CHURCH OF QUARTEROLOGY
THE TRUTHICIDE
THE FAMILY OF PANCAKE COWS
THE FAMILY OF SPHERICAL COWS
THE IMPROBABLE PACHYDERM
THE ILL-SCALING OF ALLOMETRIC BODIES
THE SUPPLY MOST FAIR
THE SUPPLY TO THE MOST
THE DARK ART OF GENERATING FUNCTIONS
THE RANDOM SUM OF RANDOMNESS
THE TWO-SIDED WORLDS
THE STORIES AND THE TROPES
THE TRUTH OF DIFFUSION
THE UNVEILING OF HIDDEN POWERS
THE SCRYING FOR THE SHAPES OF THINGS
THE LIMITS OF ORGANIZATIONS
THE OVERCOMING OF CATASTROPHE
THE TROUBLES ILL-FORMED
THE NETWORKS OF MANY ILKS
THE CHAOS OF FETTERED CONTAGION
THE END


THE SOCIAL CONTAGION

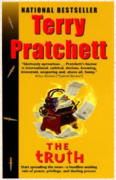
'The rumor spread through the city like wildfire




"The Truth"
by Terry Pratchett (2000). [22]



'The rumor spread through the city like wildfire which had quite often spread through Ankh-Morpork

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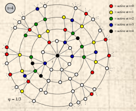
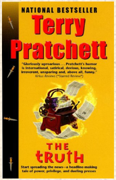


'The rumor spread through the city like wildfire which had quite often spread through Ankh-Morpork since its citizens had learned the words

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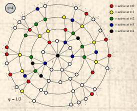
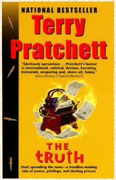


'The rumor spread through the city like wildfire which had quite often spread through Ankh-Morpork since its citizens had learned the words "fire insurance").'

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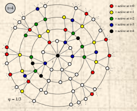

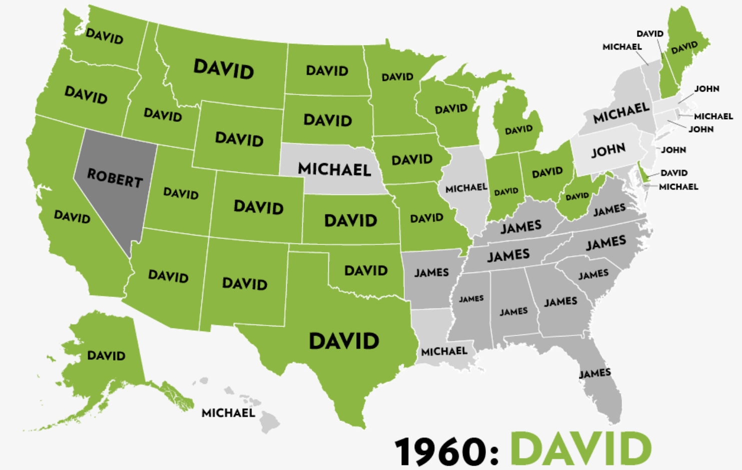


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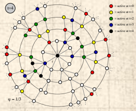

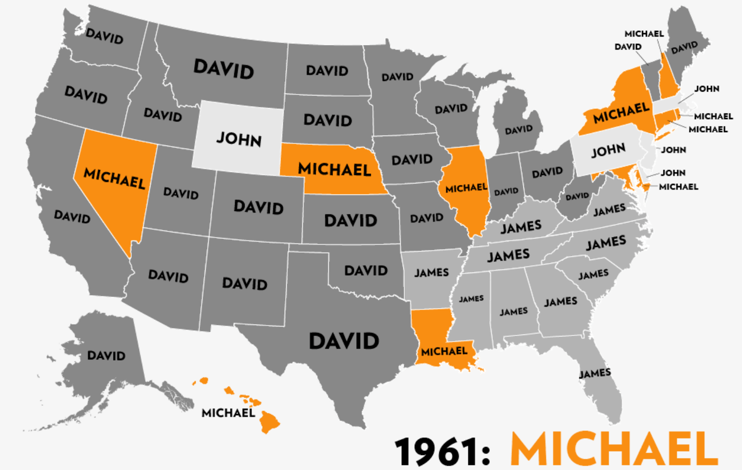


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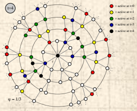

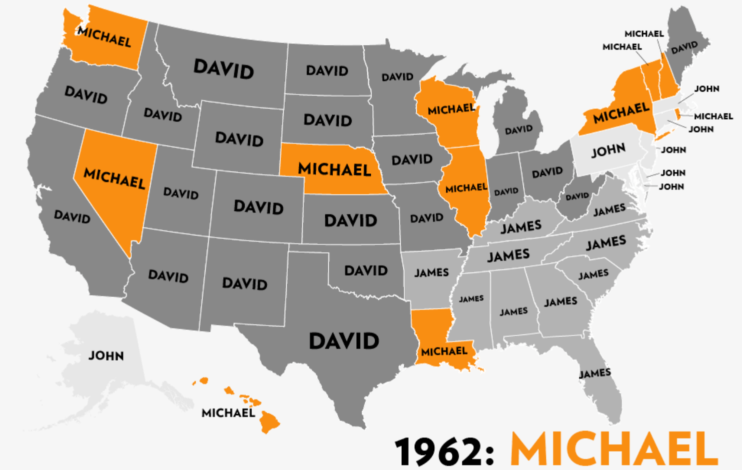


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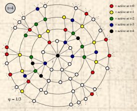

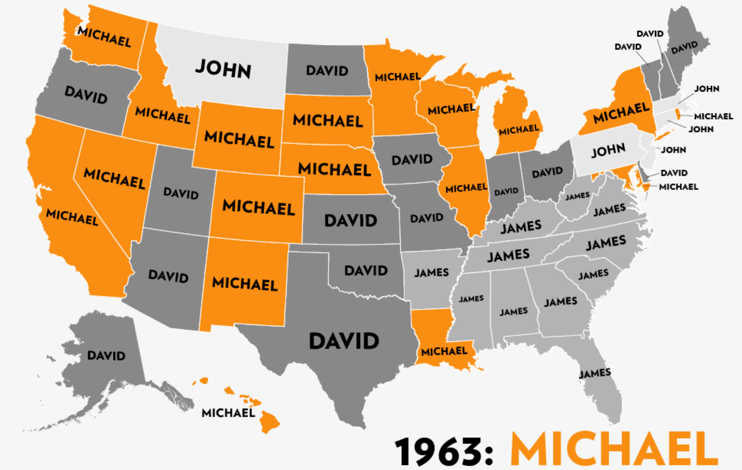


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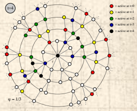

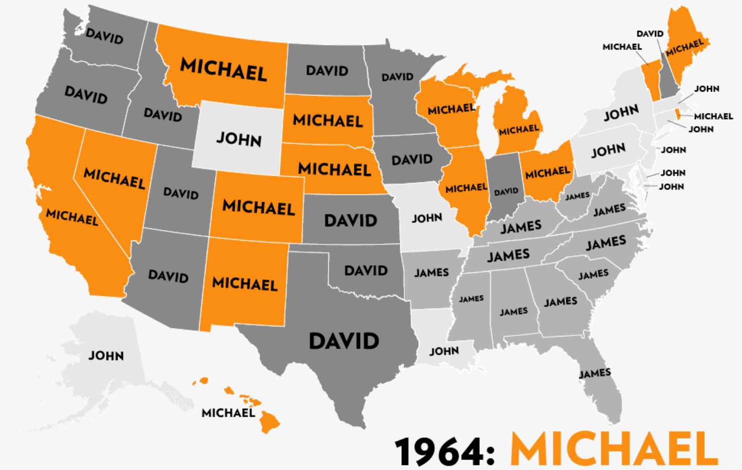


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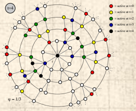

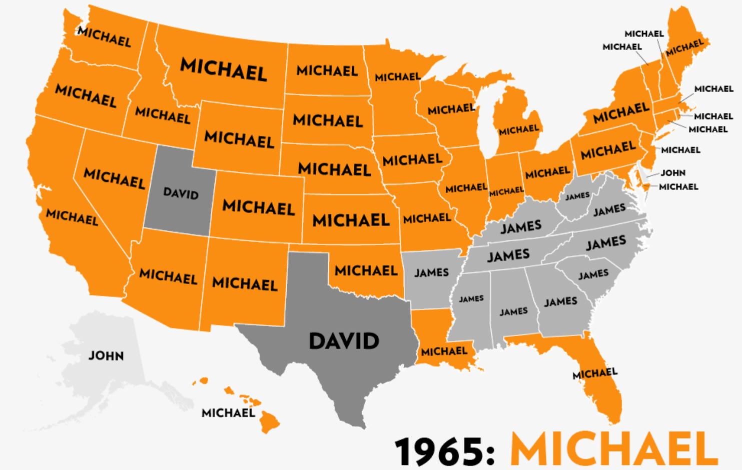


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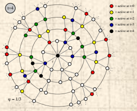

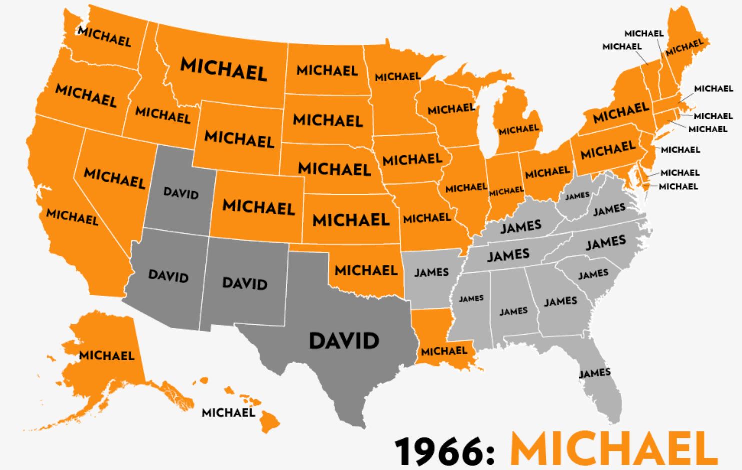


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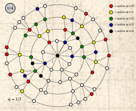

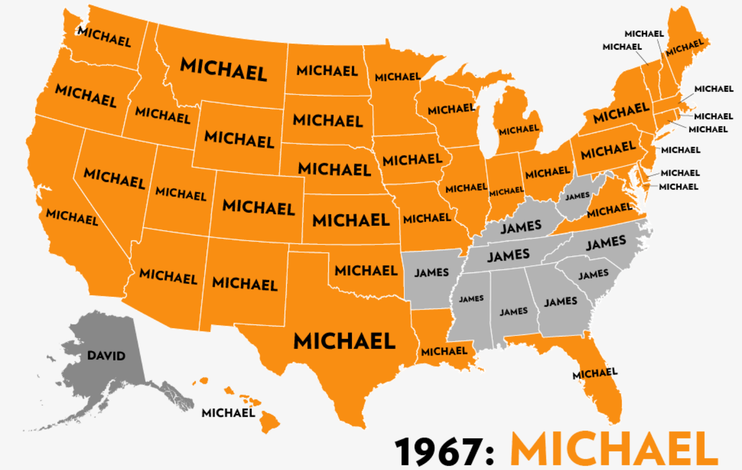


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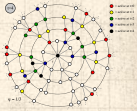

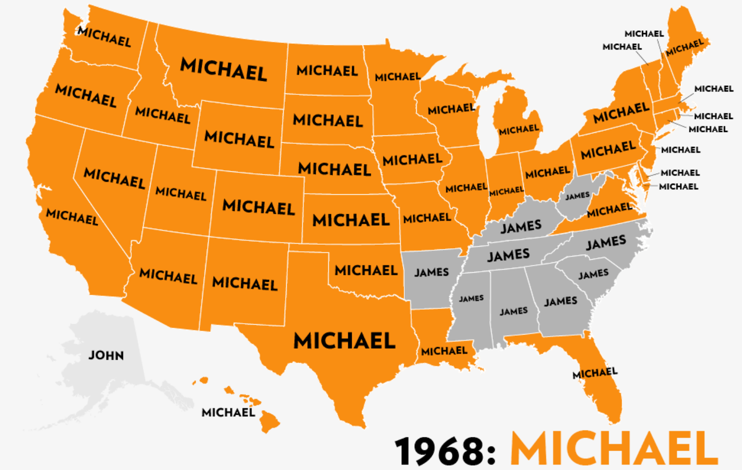


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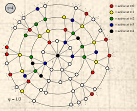

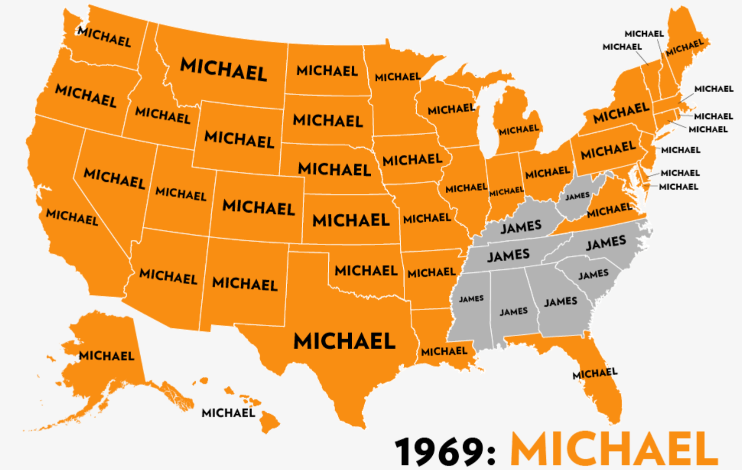


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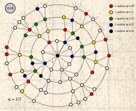

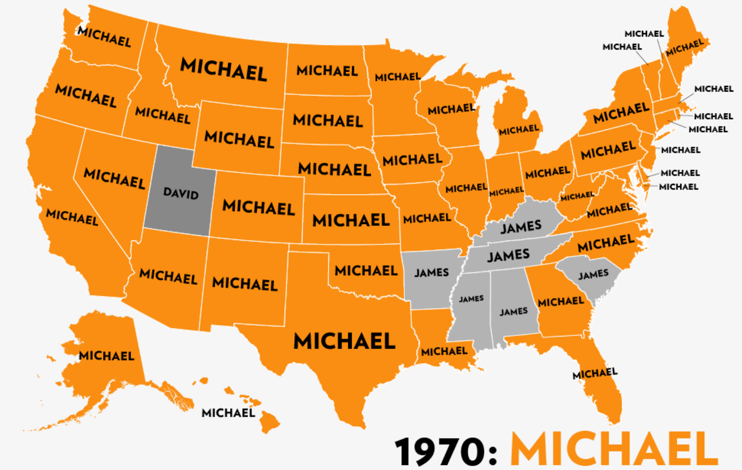


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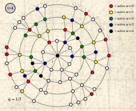

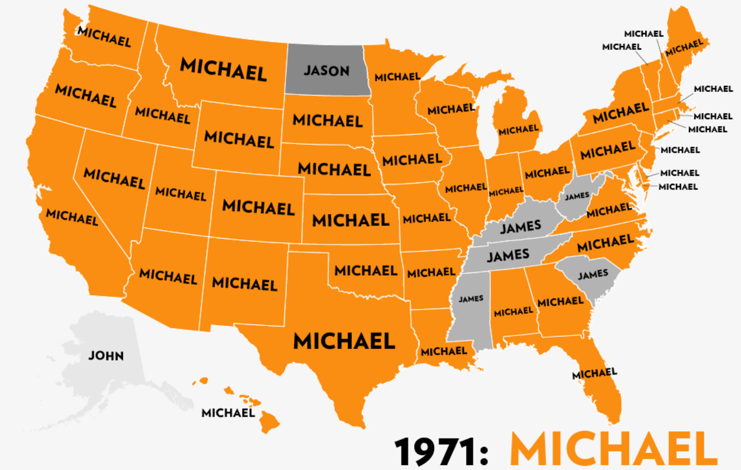


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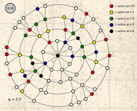

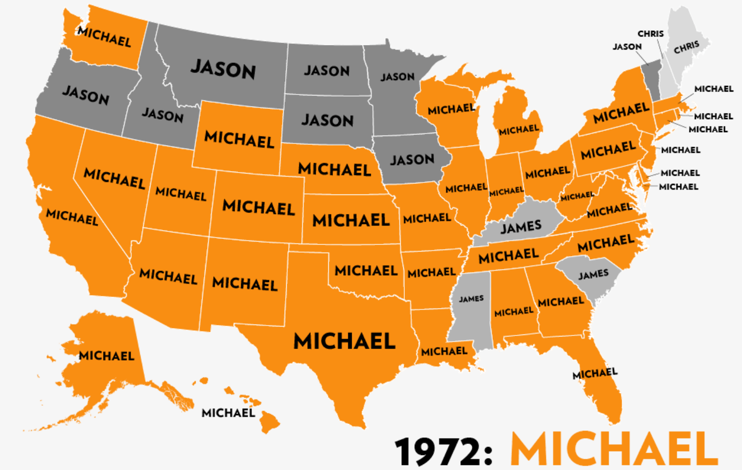


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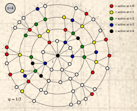

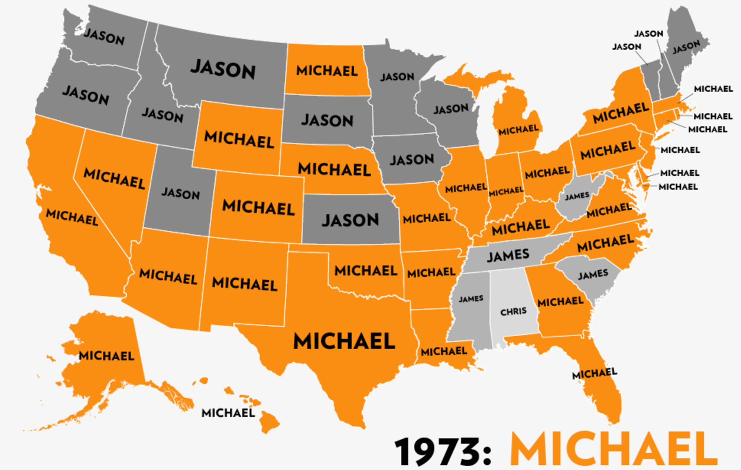


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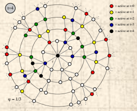

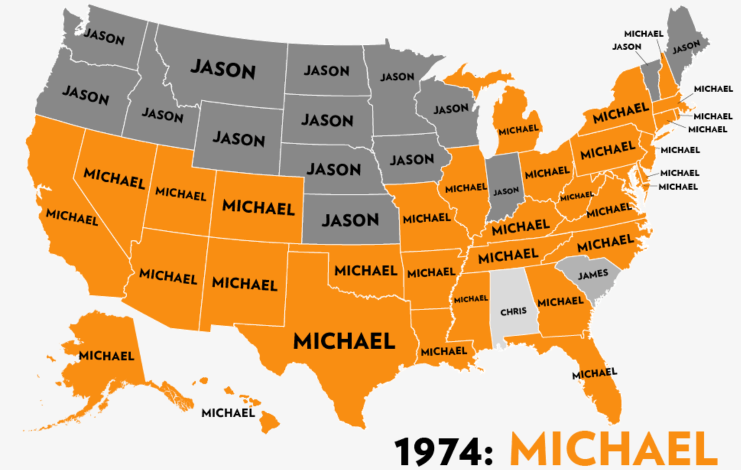


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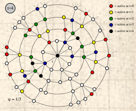

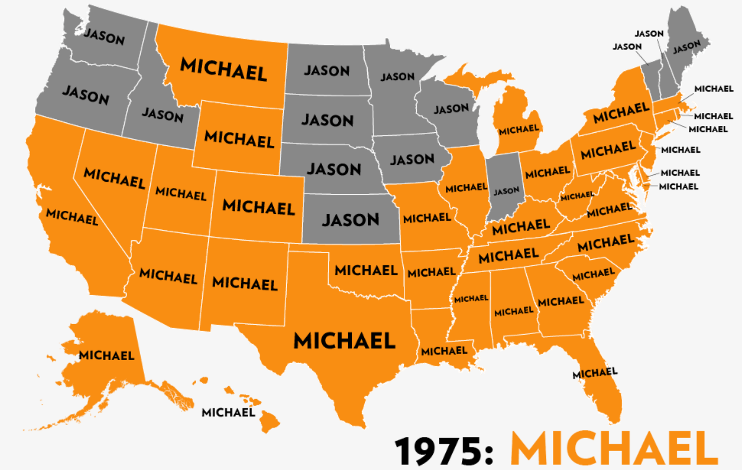


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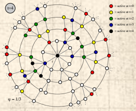

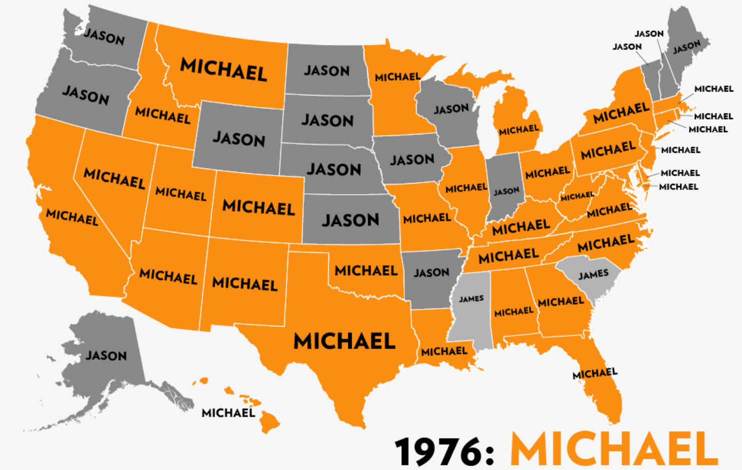


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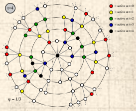

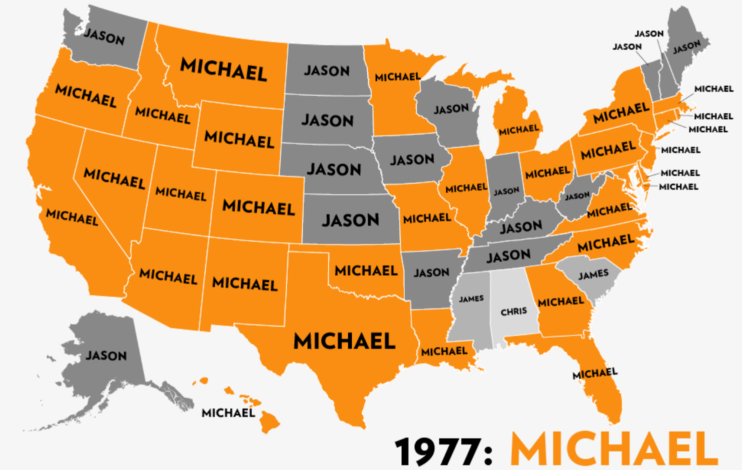


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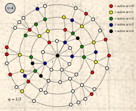

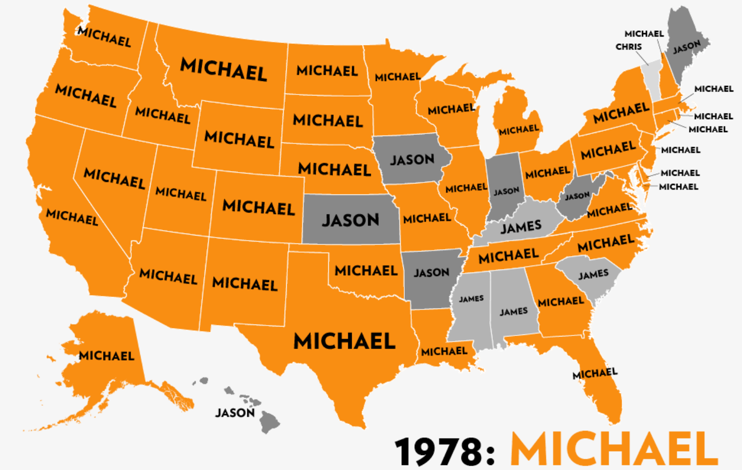


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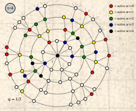

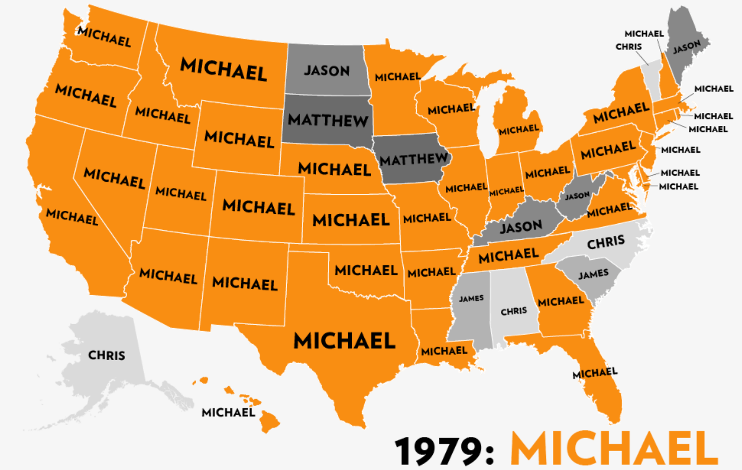


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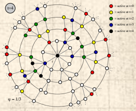
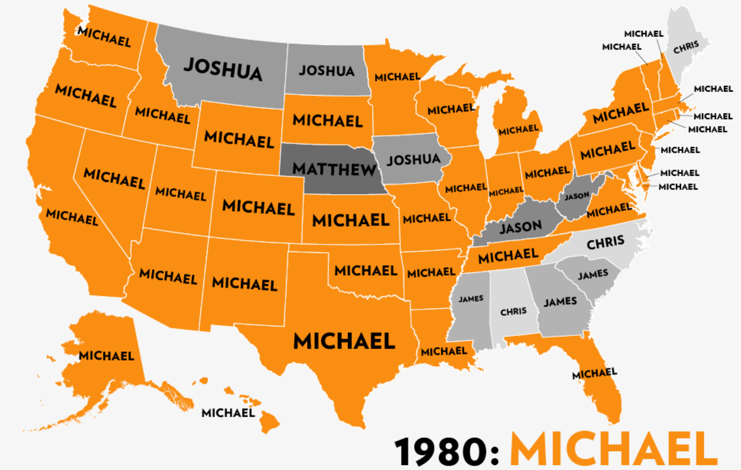
Social Contagion Models
Background
Granovetter's model
Network version
Final size
Spreading success
Groups
References



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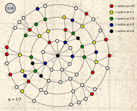

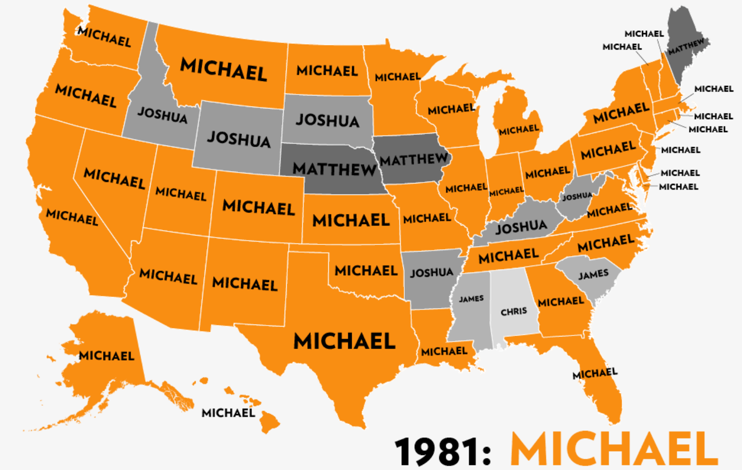


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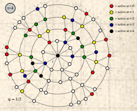

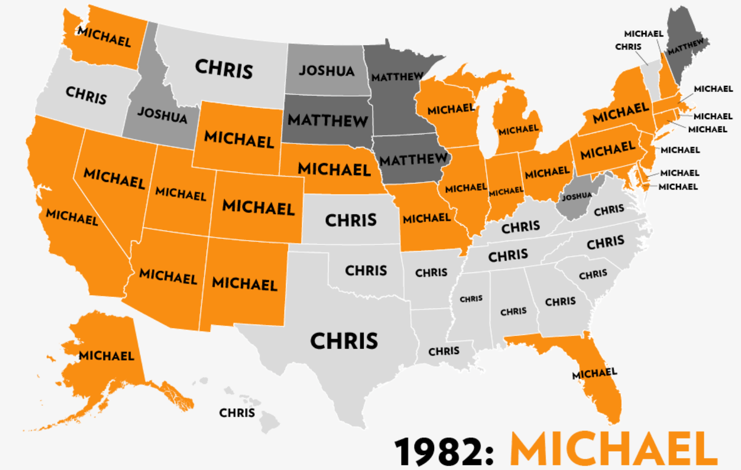


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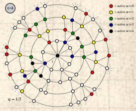

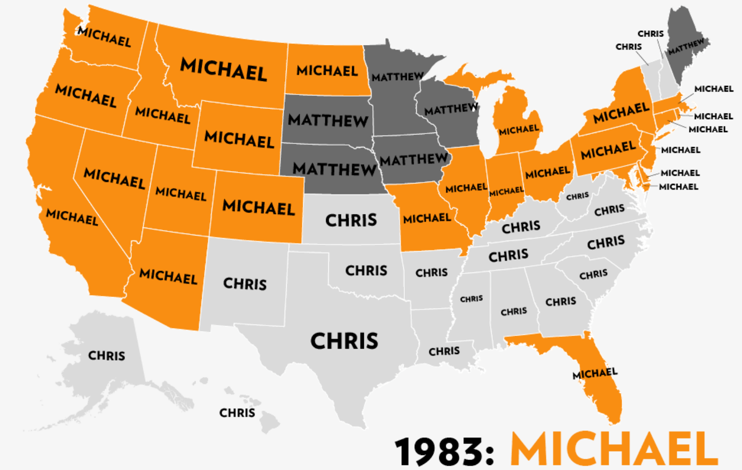


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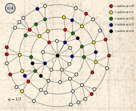

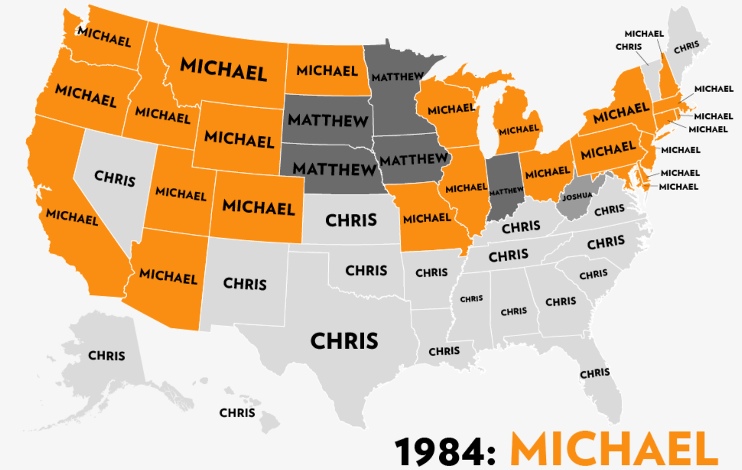


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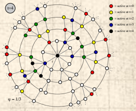

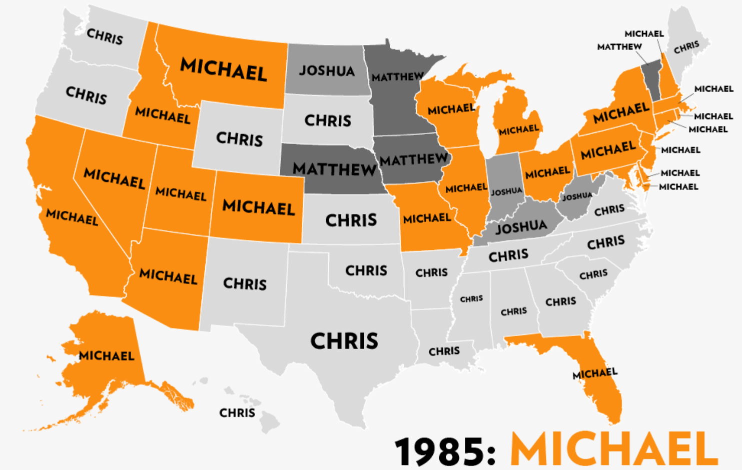


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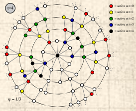

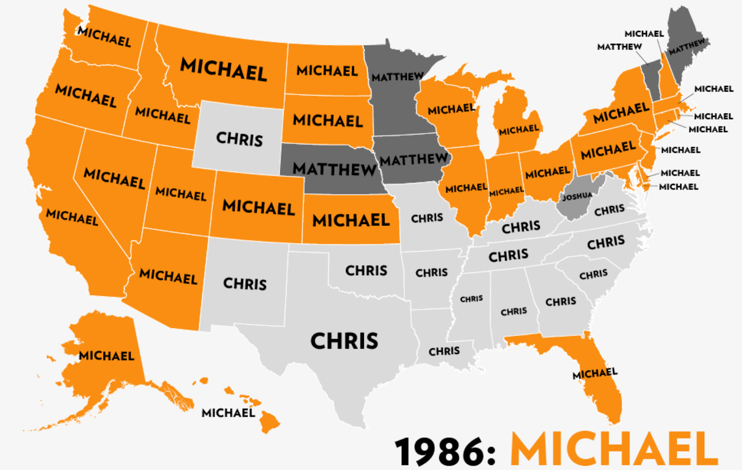


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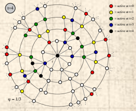

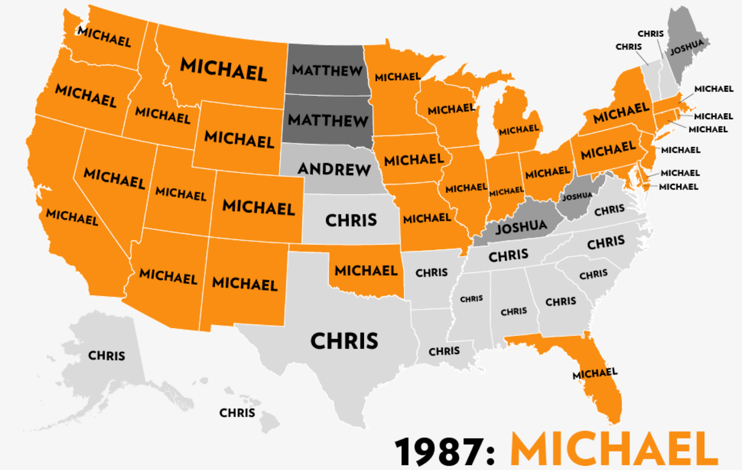


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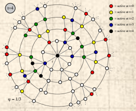

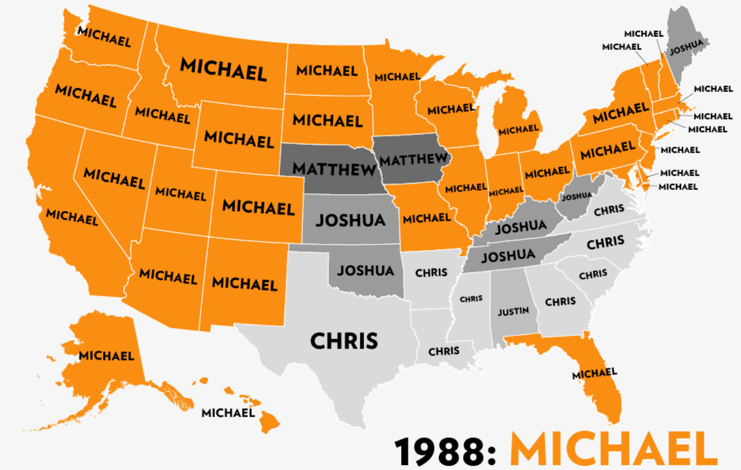


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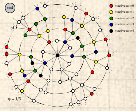

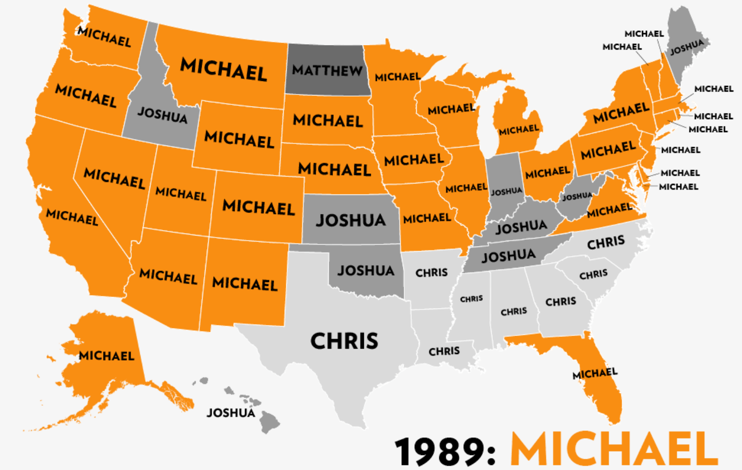


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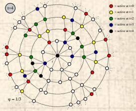

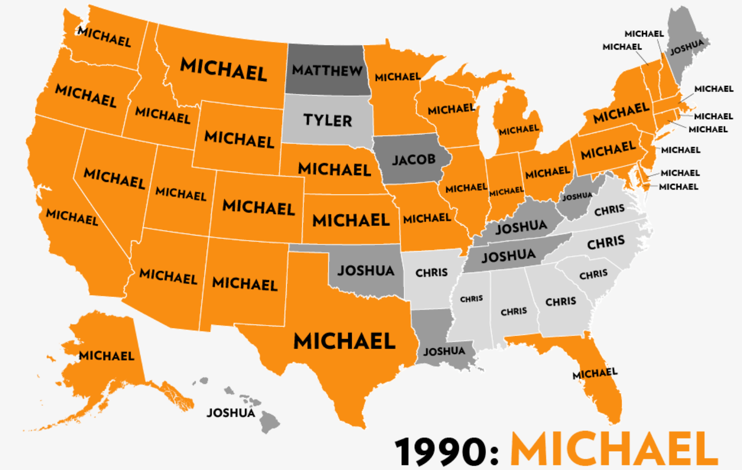


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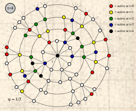

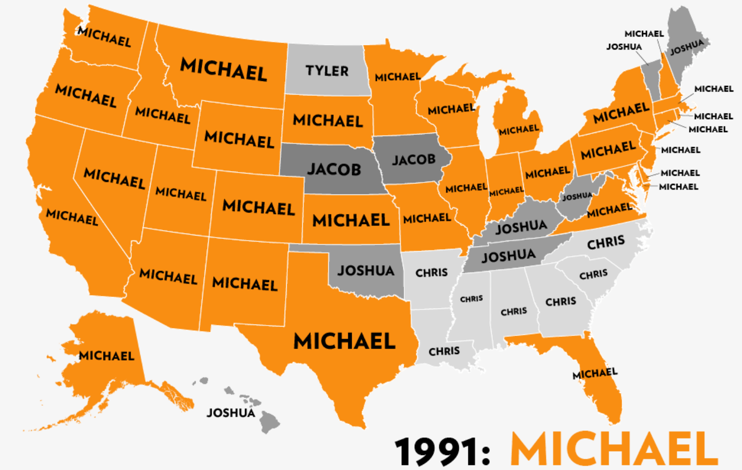


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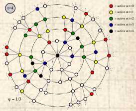

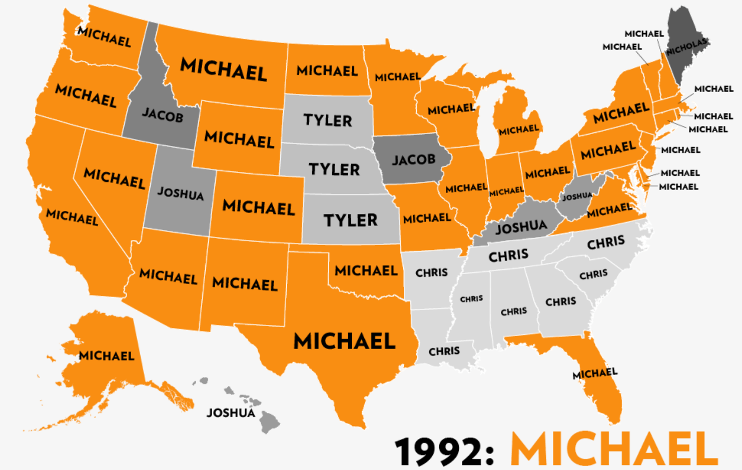


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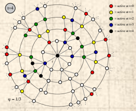

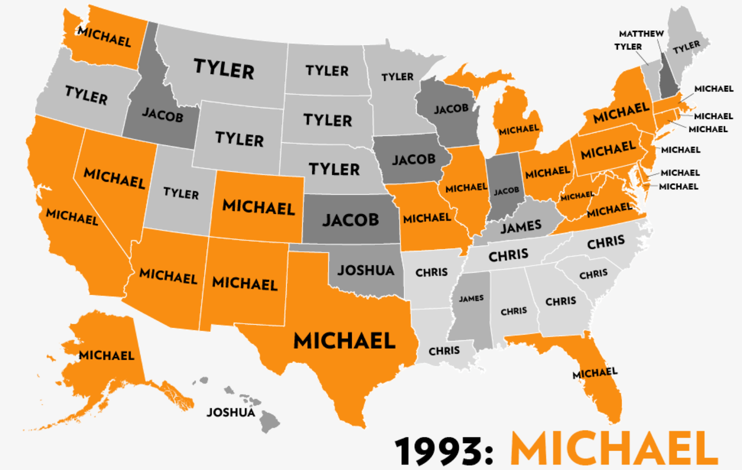


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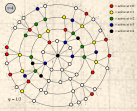

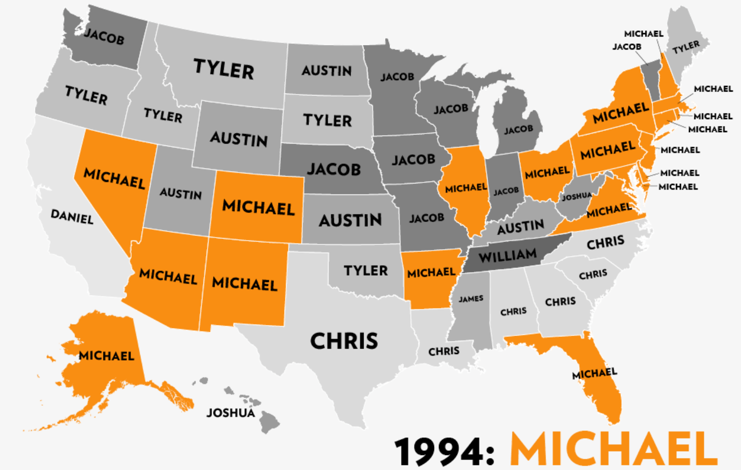


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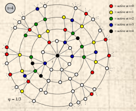

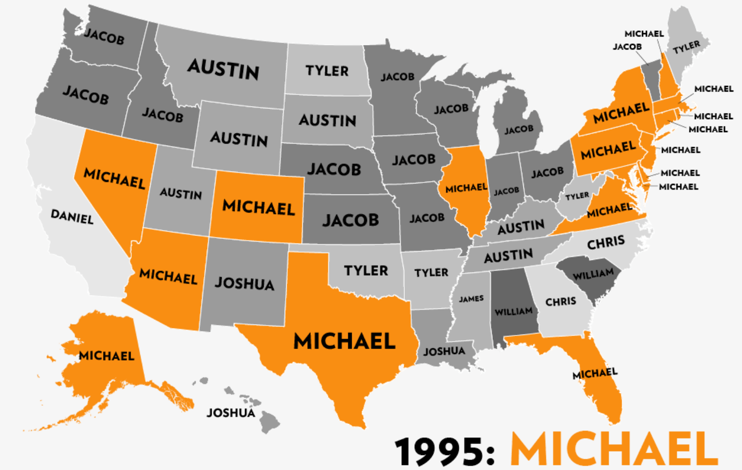


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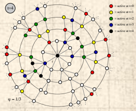

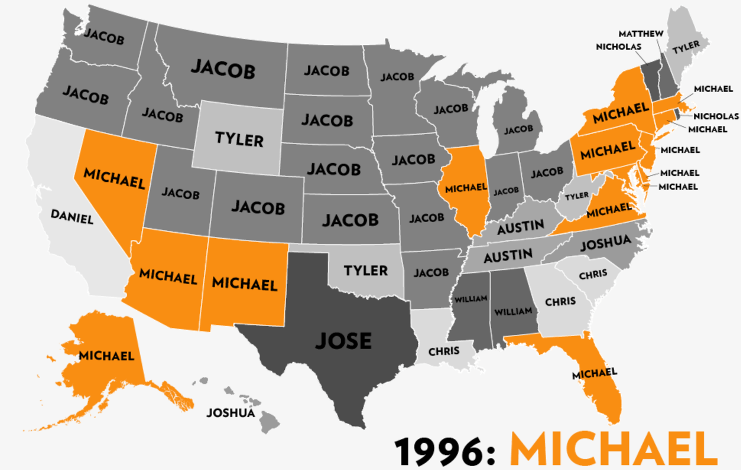


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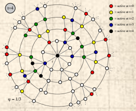

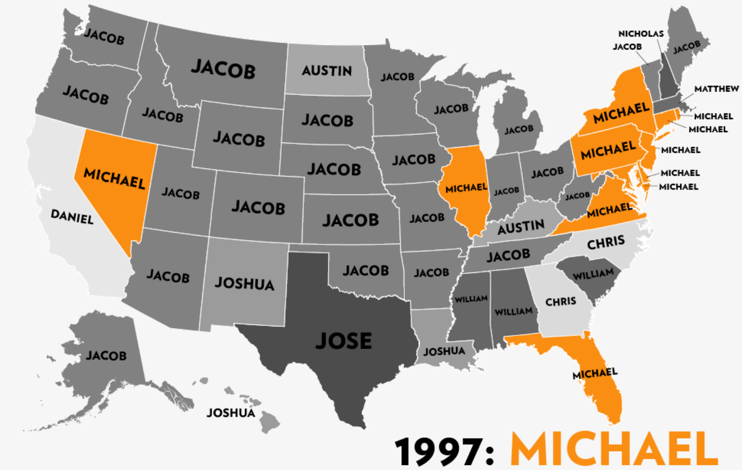


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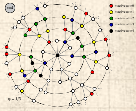

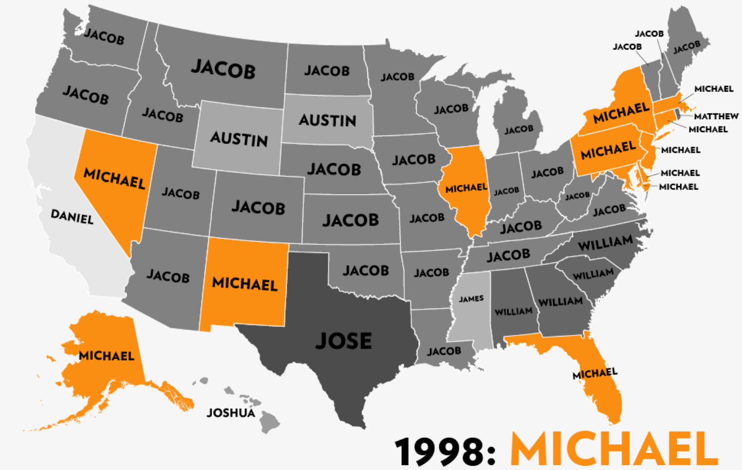


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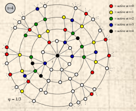

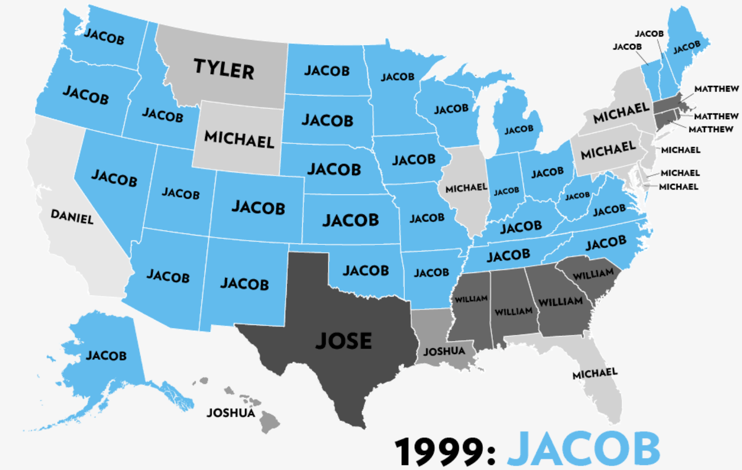


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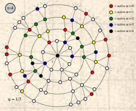

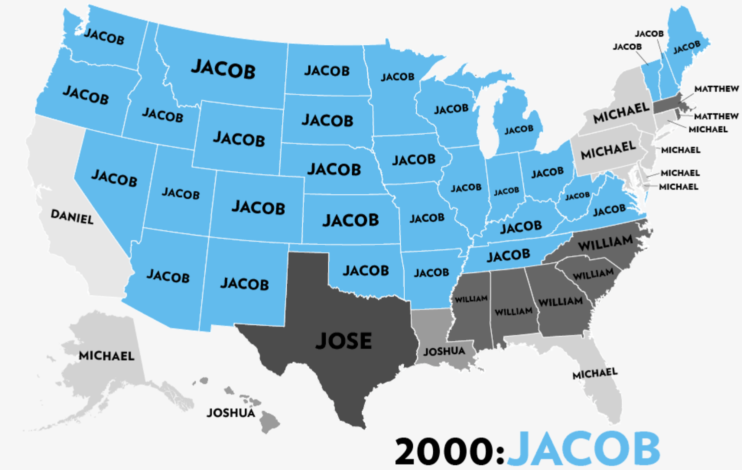


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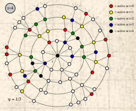

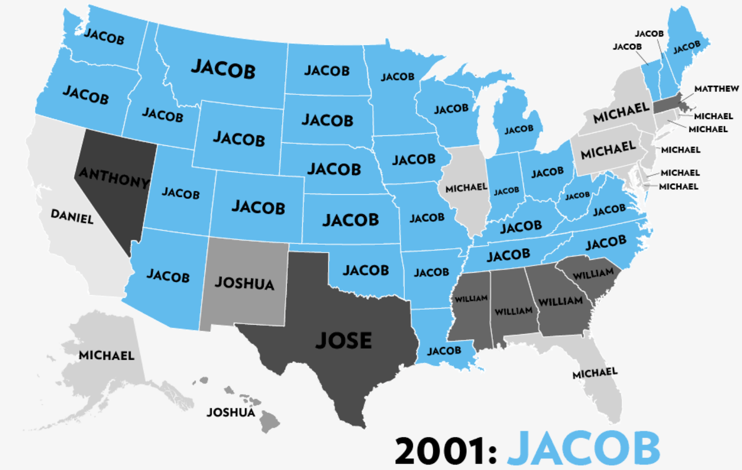


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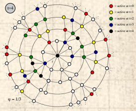

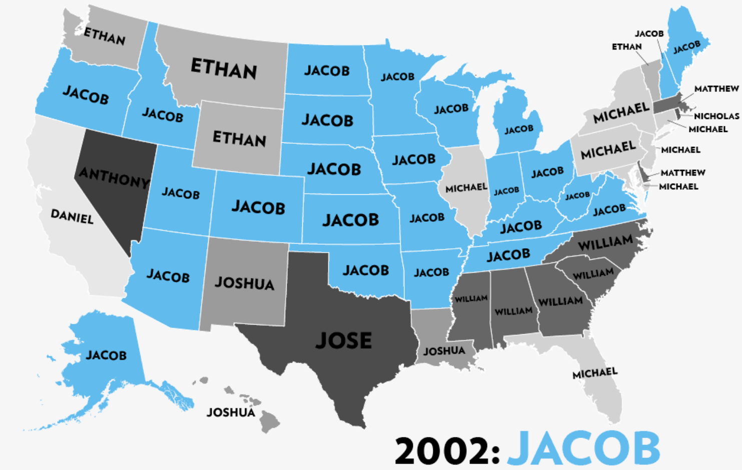


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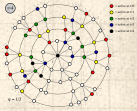

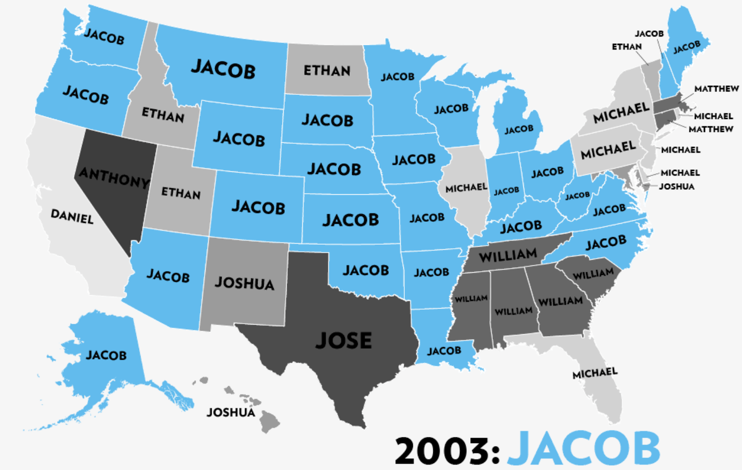


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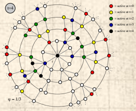

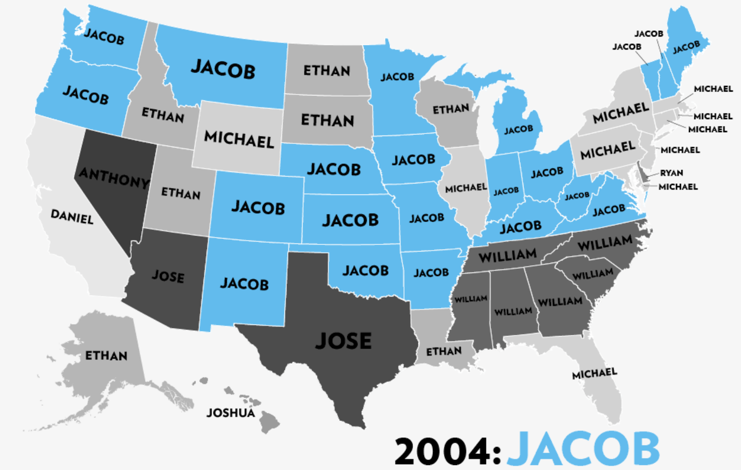


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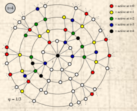

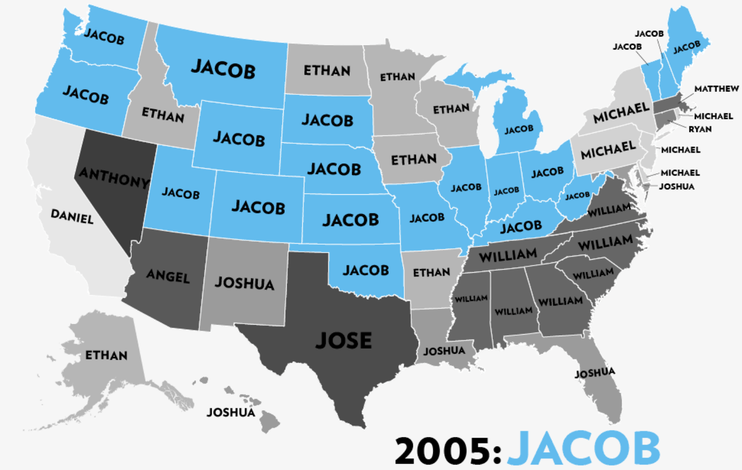


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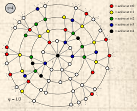

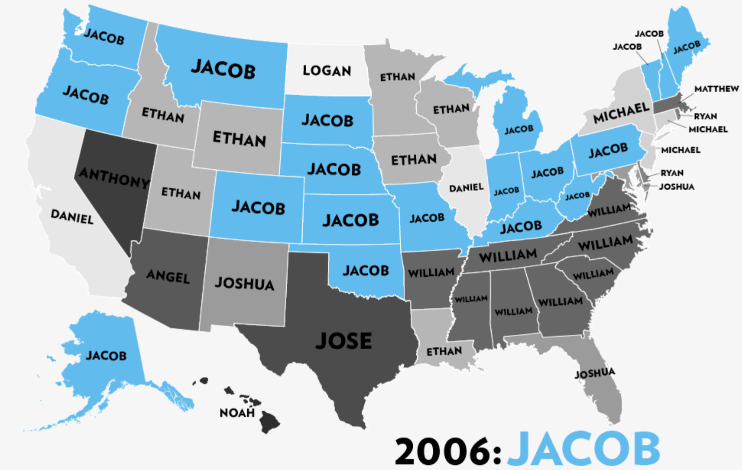


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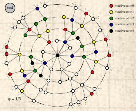

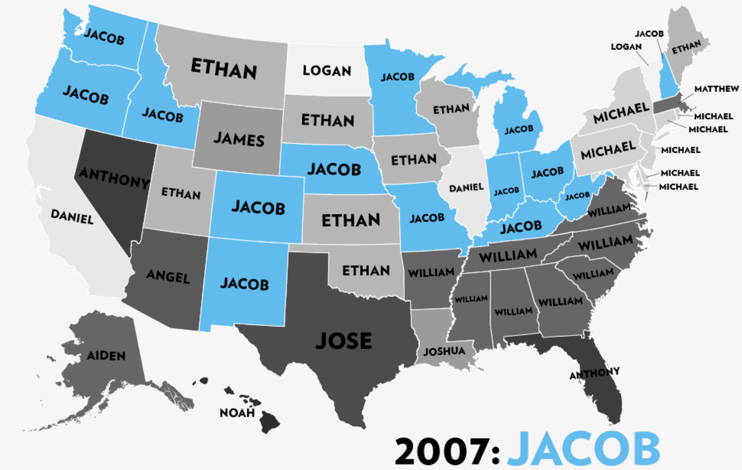


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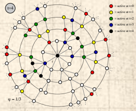

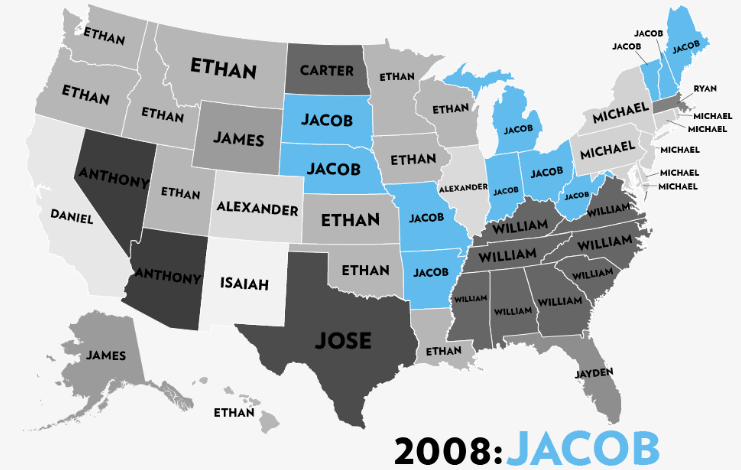


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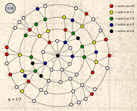

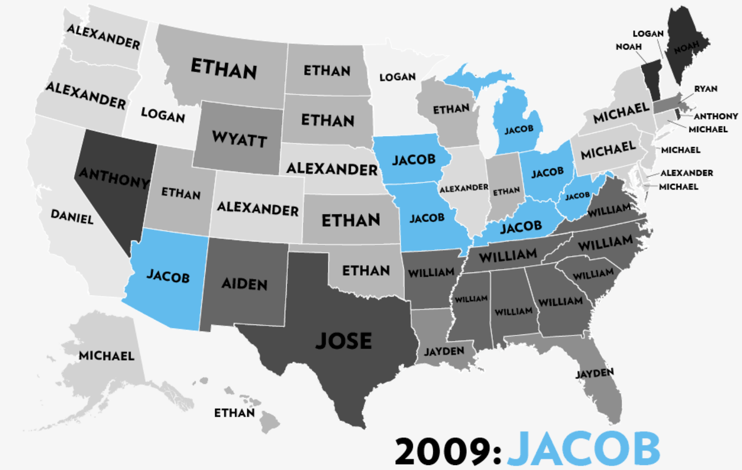


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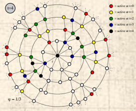

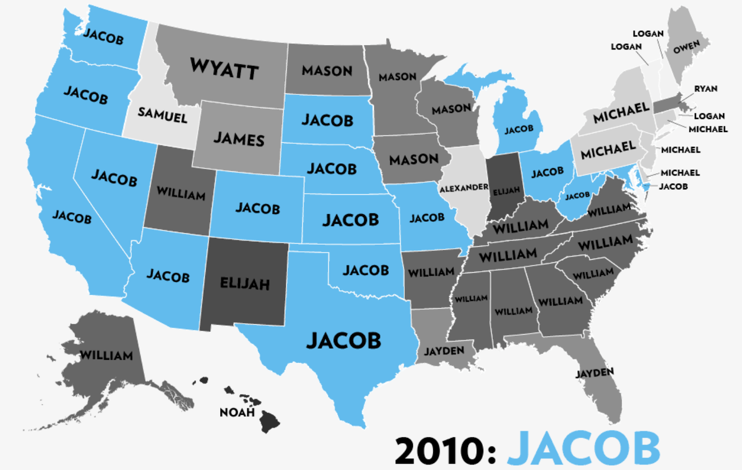


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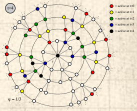

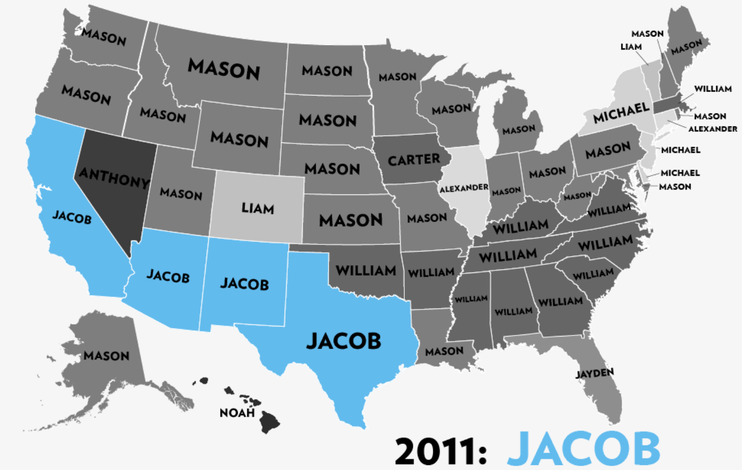


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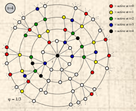


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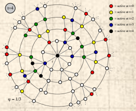

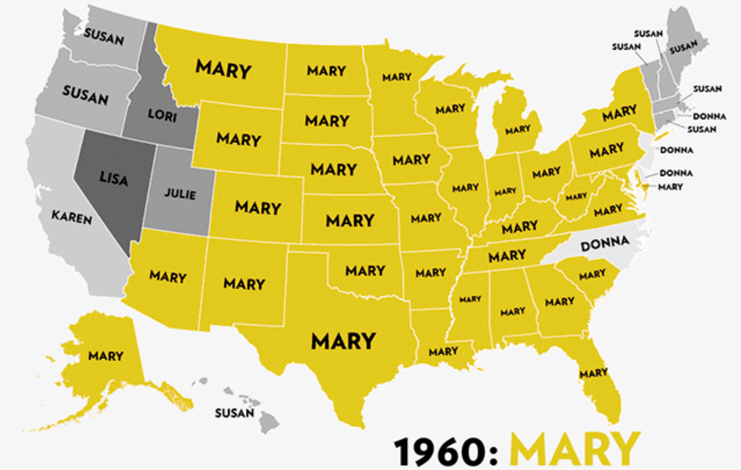


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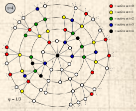

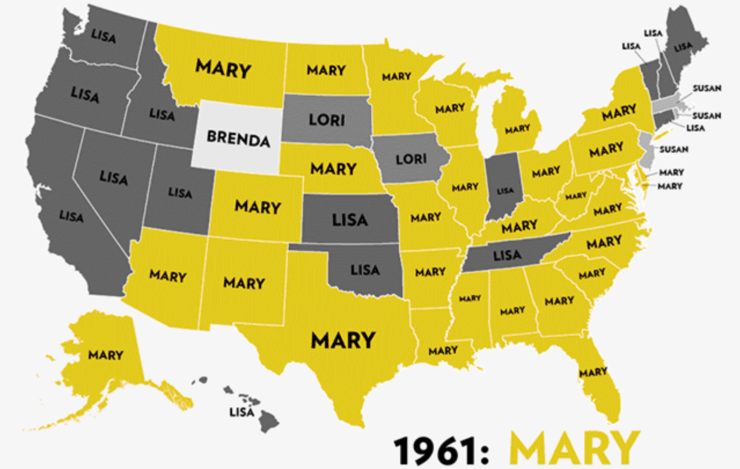


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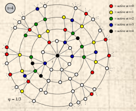

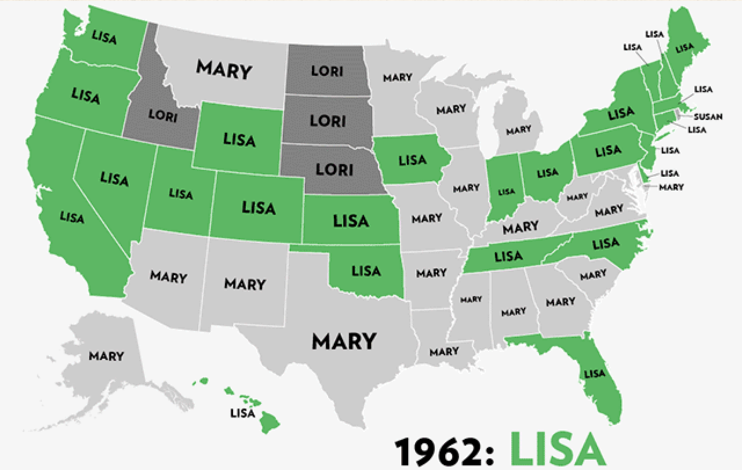


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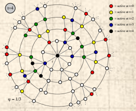

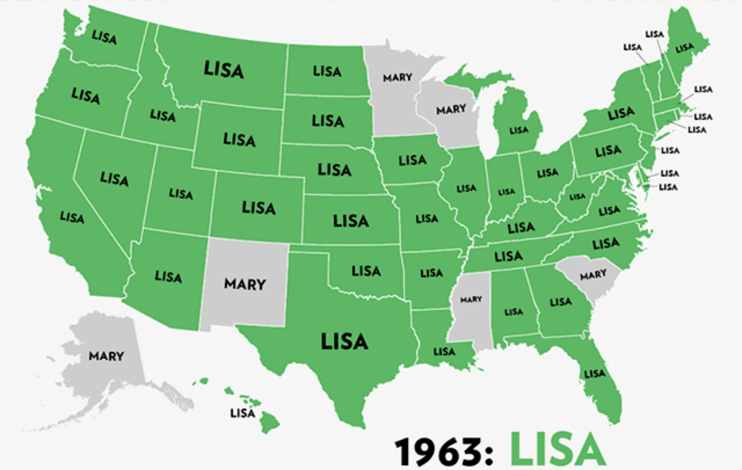


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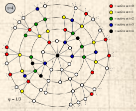

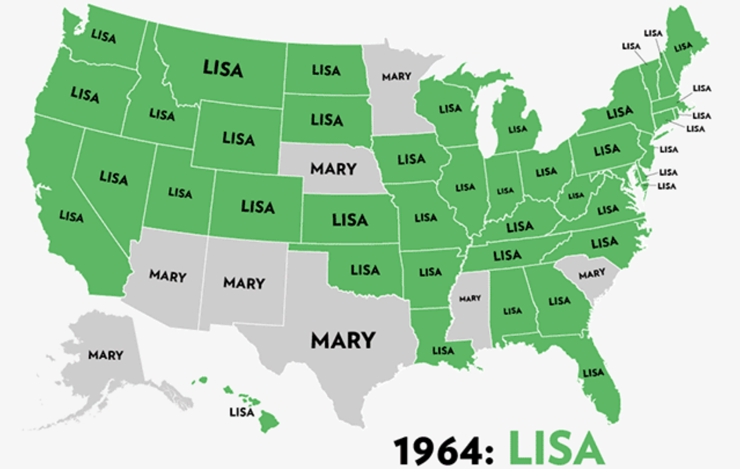


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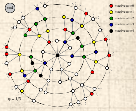

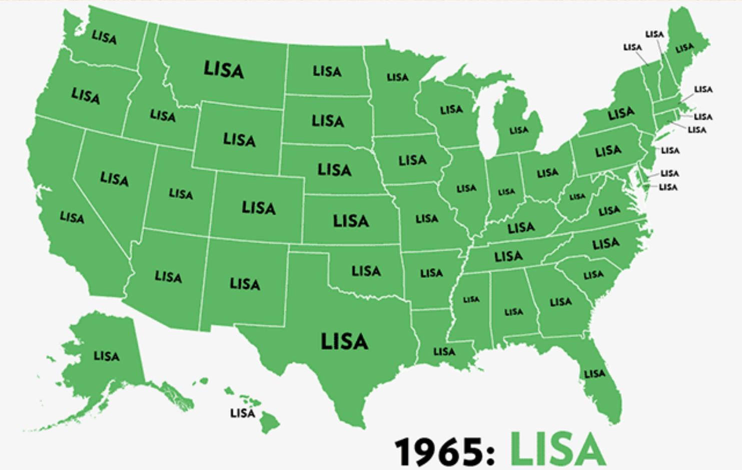


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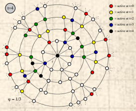

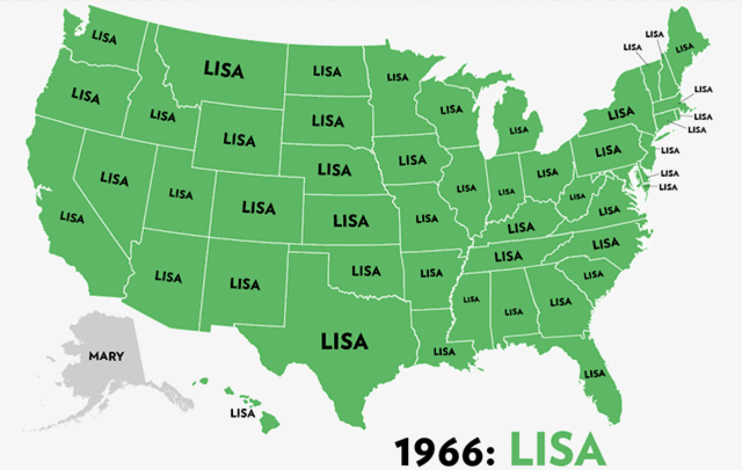


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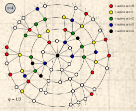

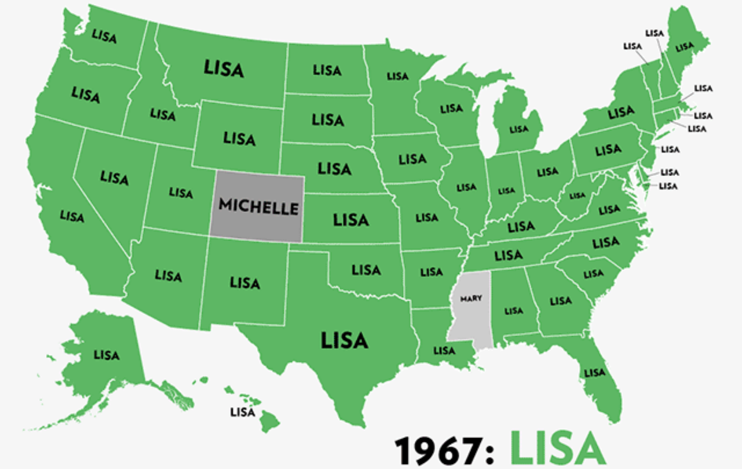


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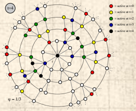

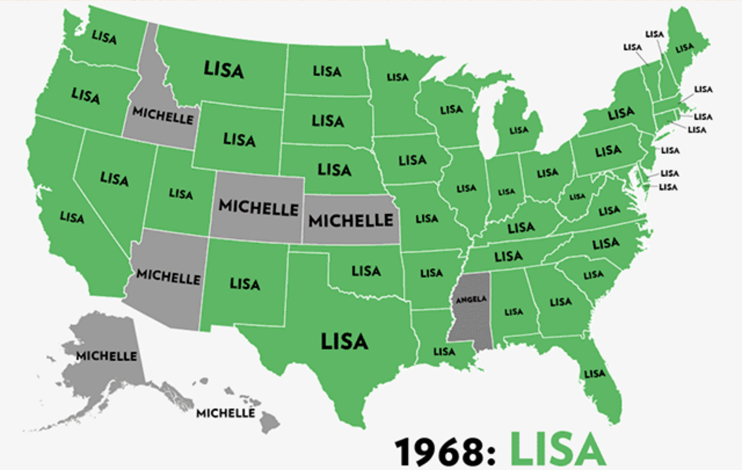


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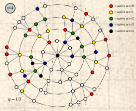

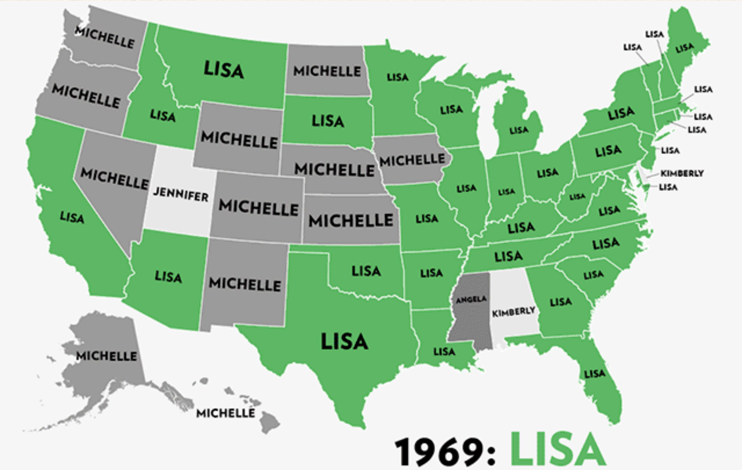


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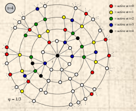

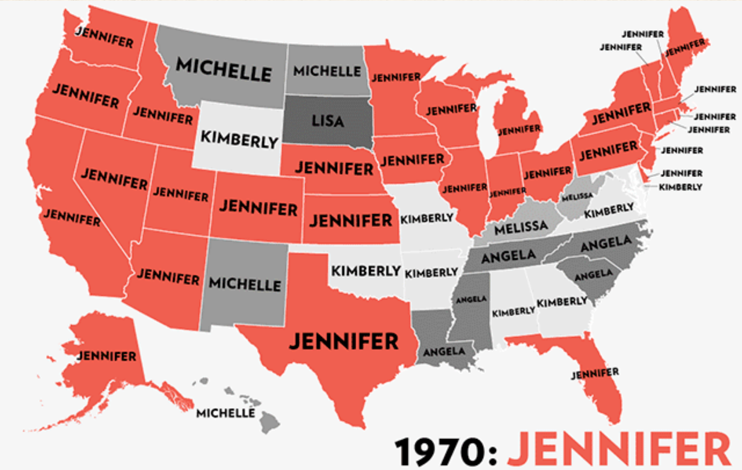


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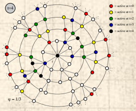

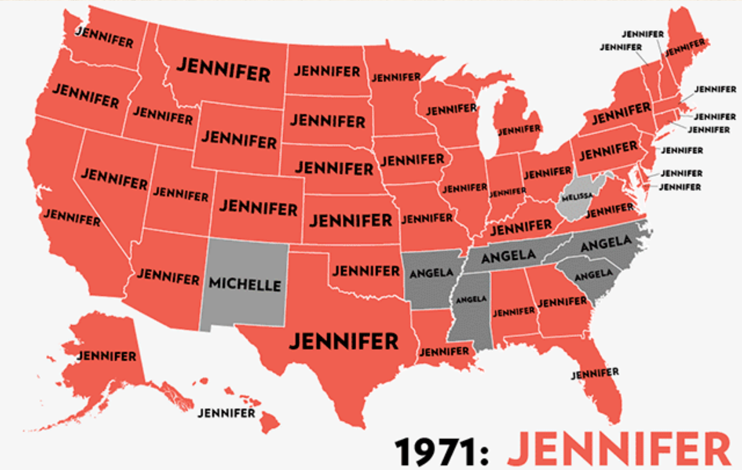


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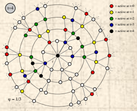

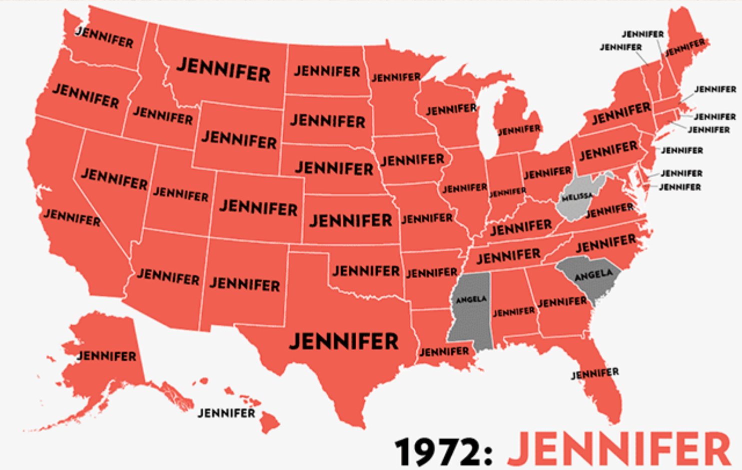


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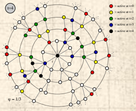

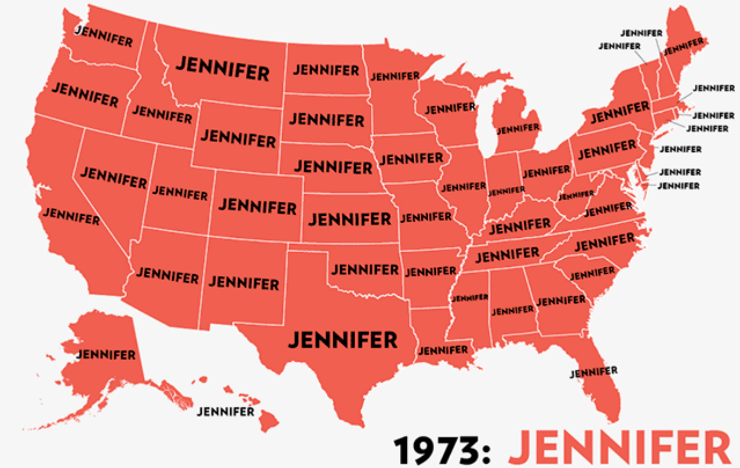


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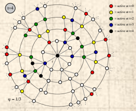

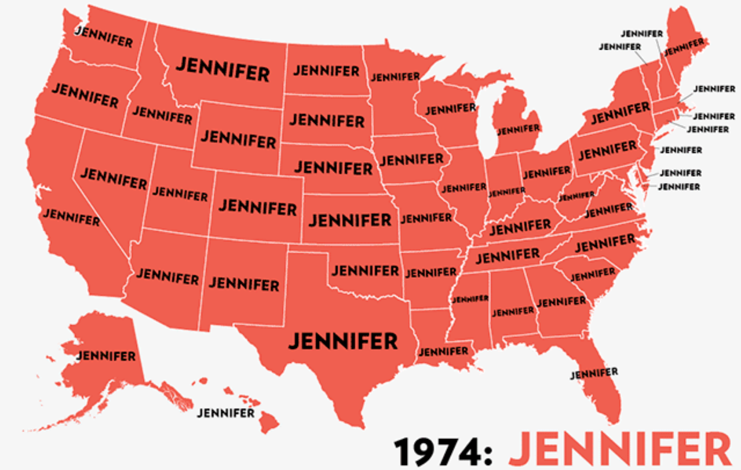


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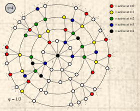

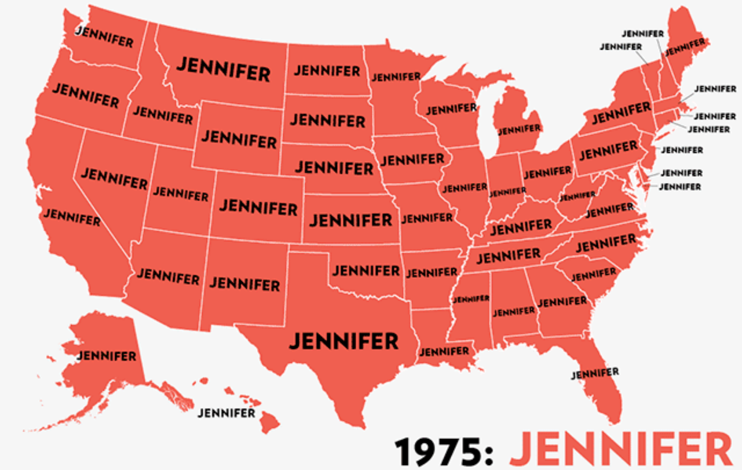


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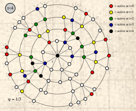

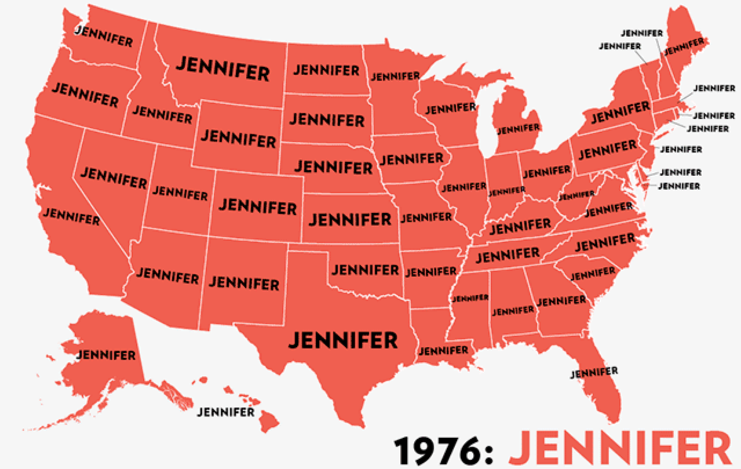


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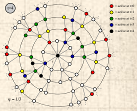

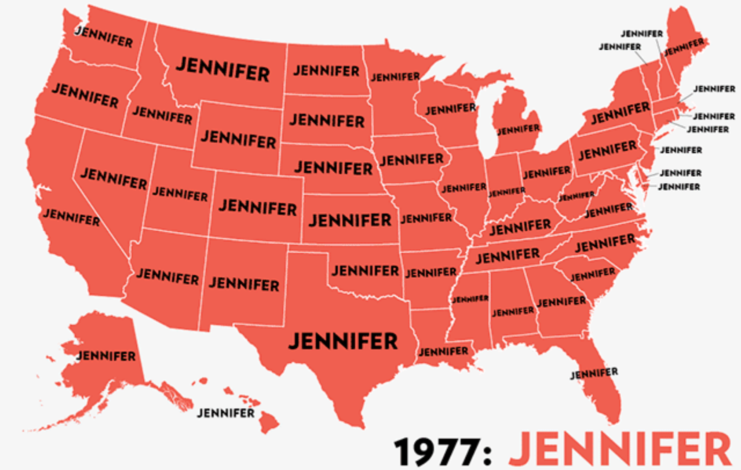


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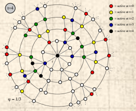

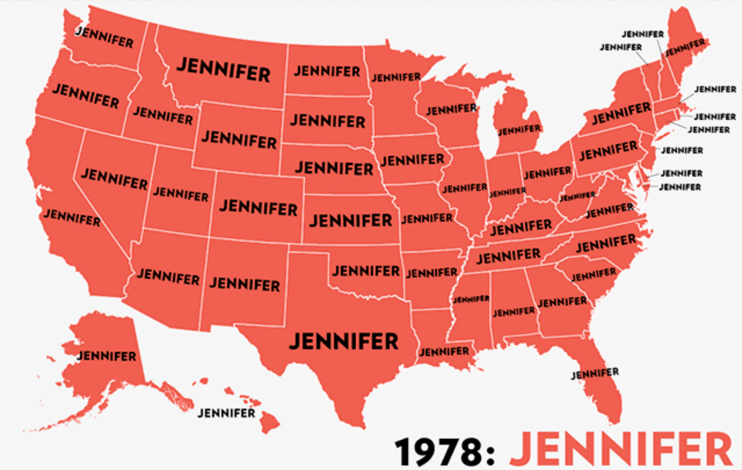


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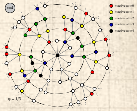

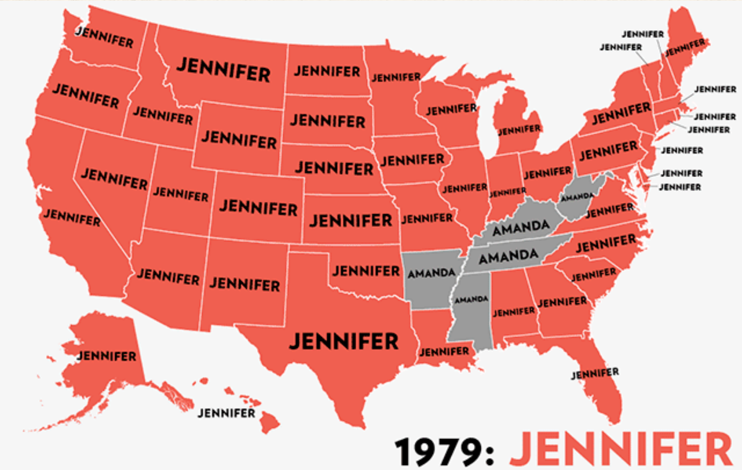


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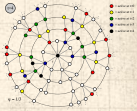

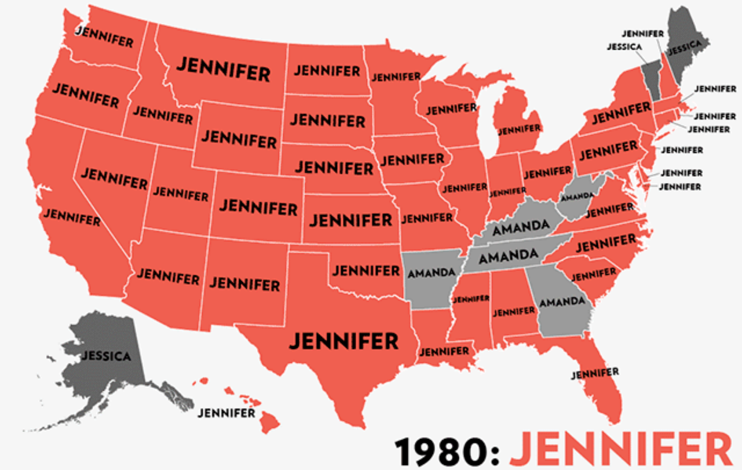


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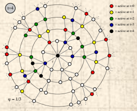

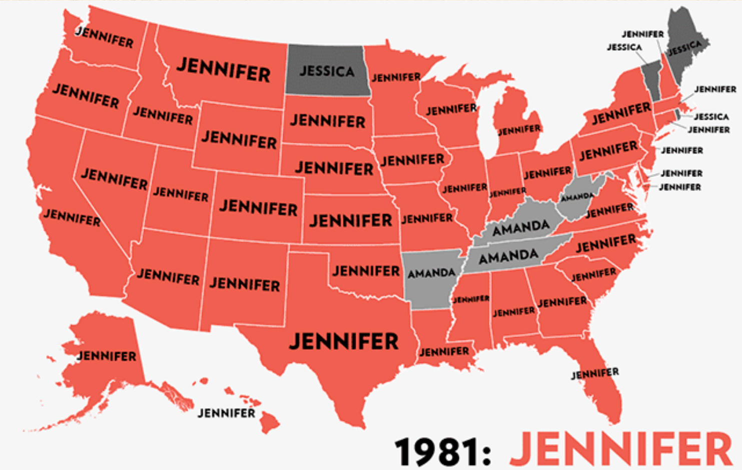


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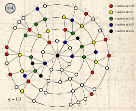

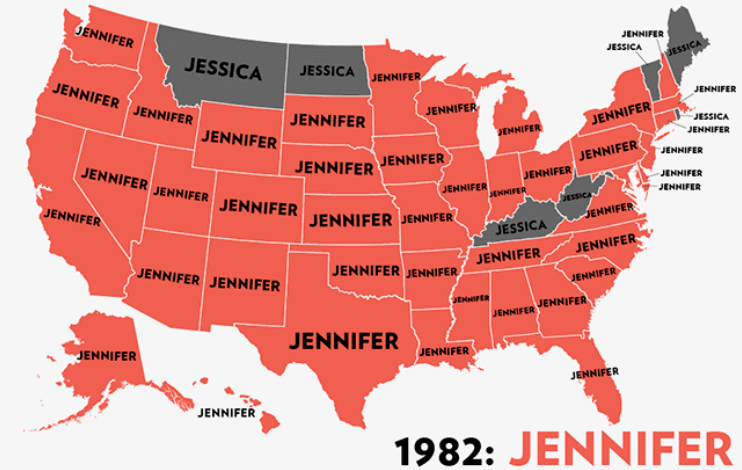


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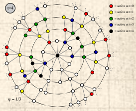

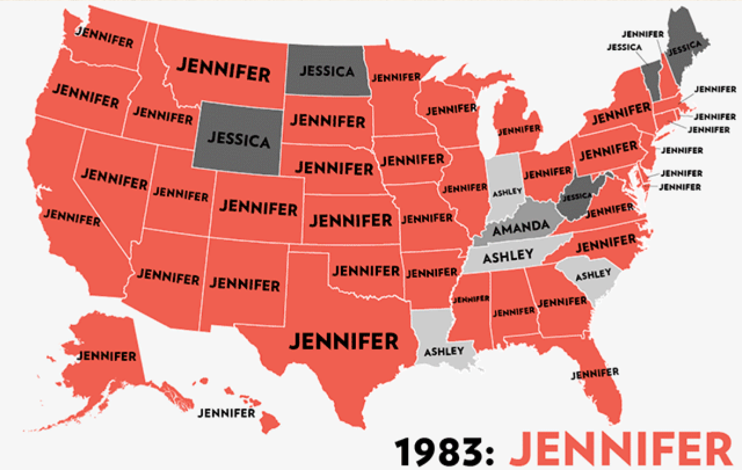


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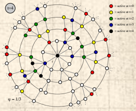

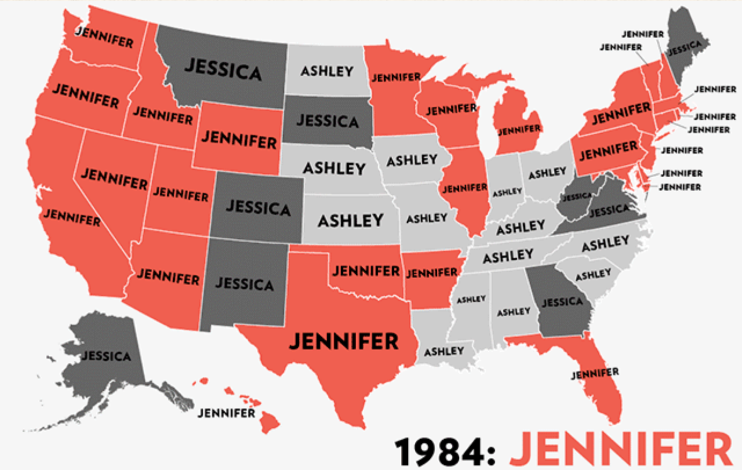


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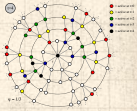

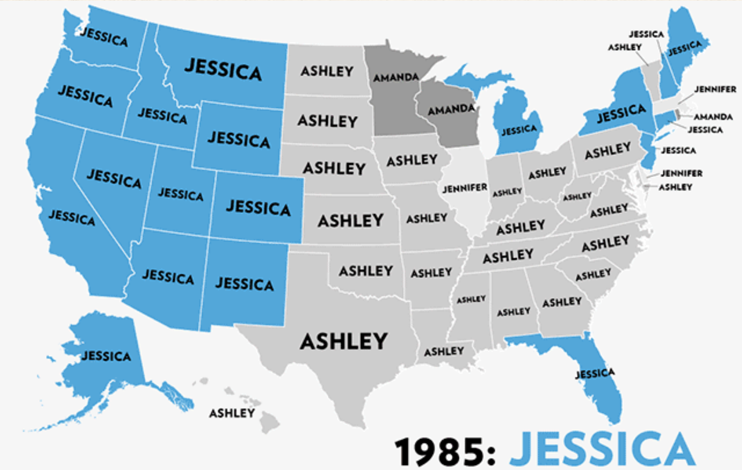


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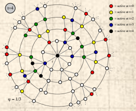

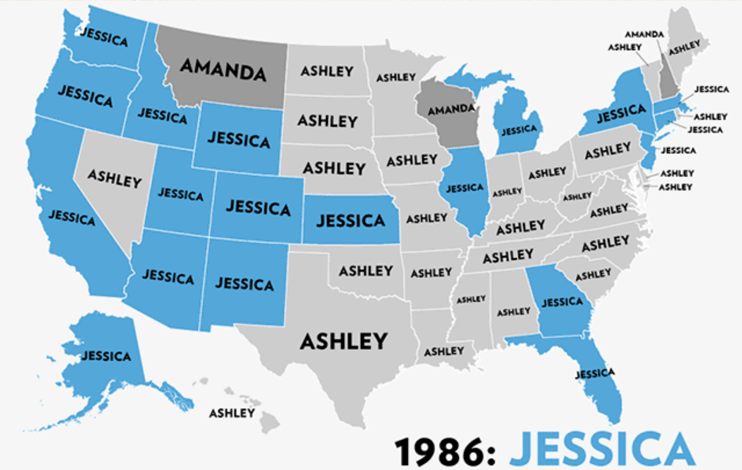


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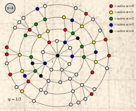

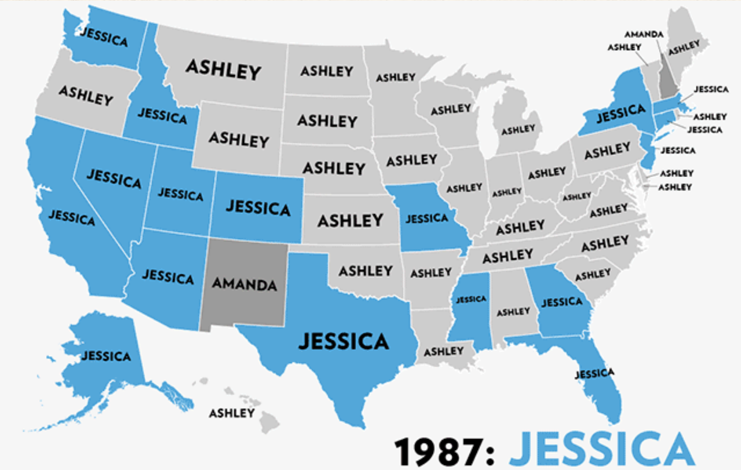


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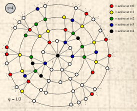

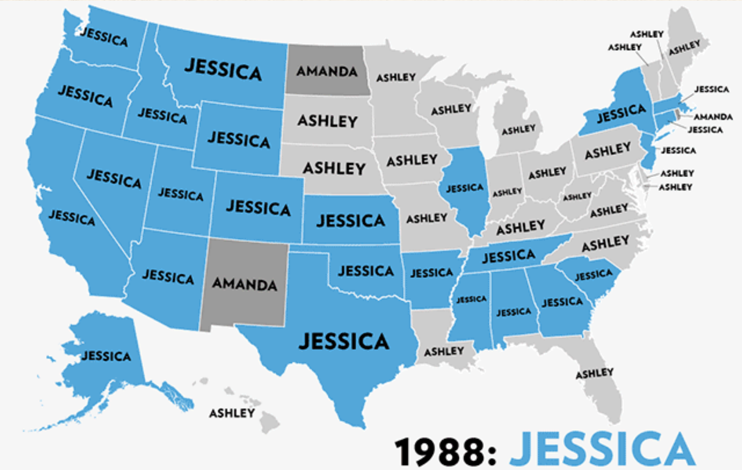


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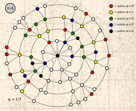

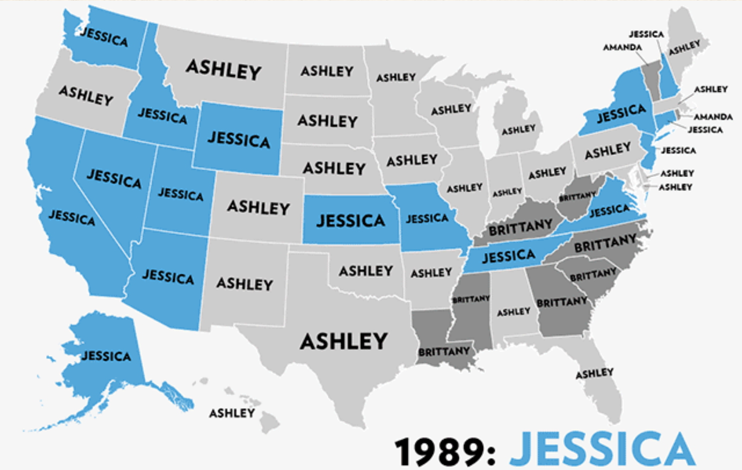


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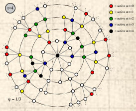

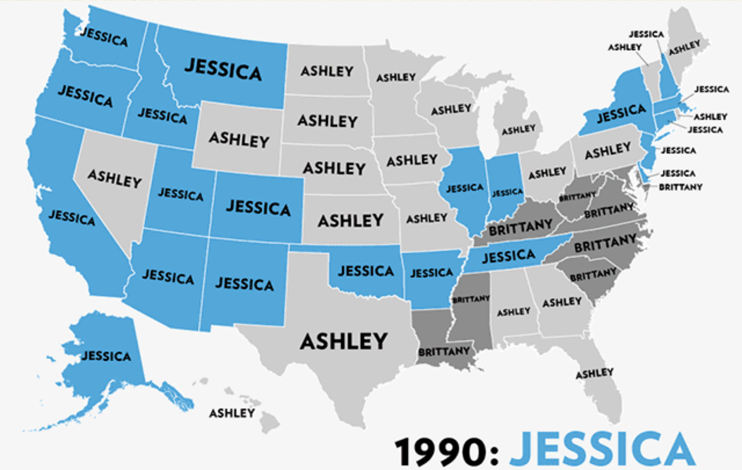


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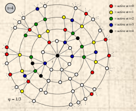

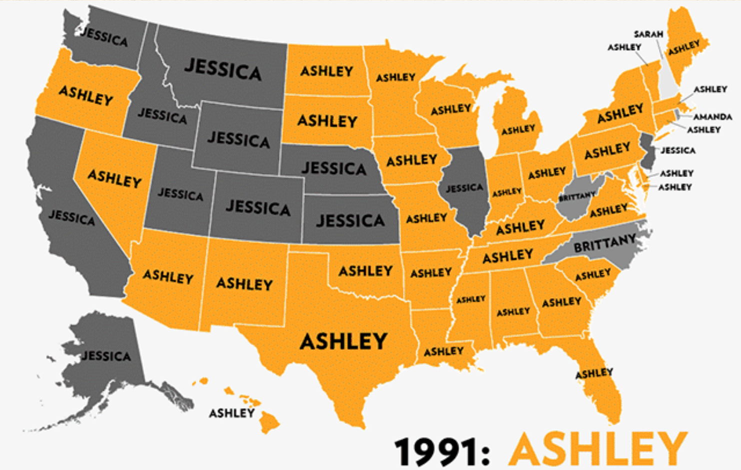


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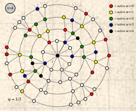


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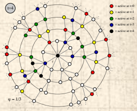

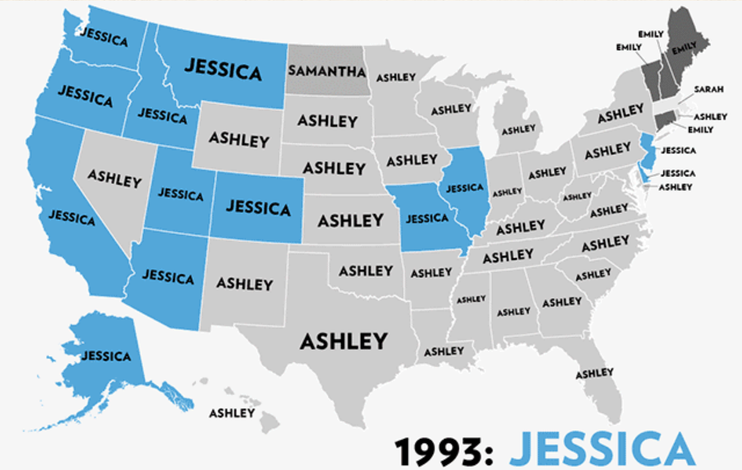


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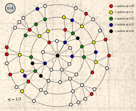

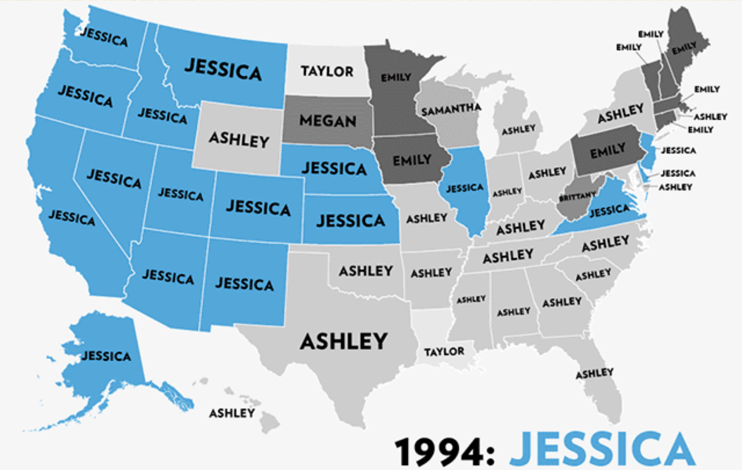


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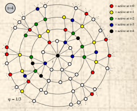

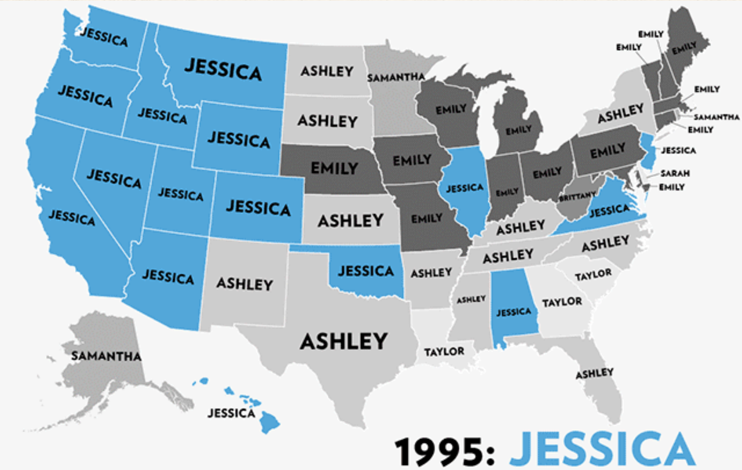


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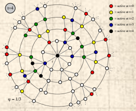

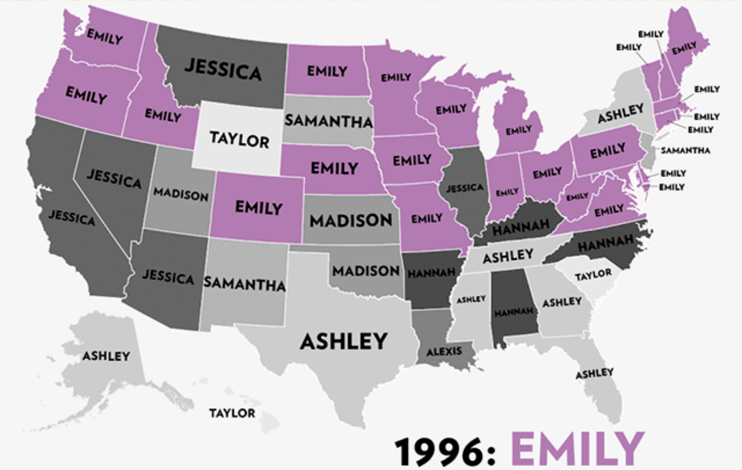


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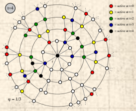

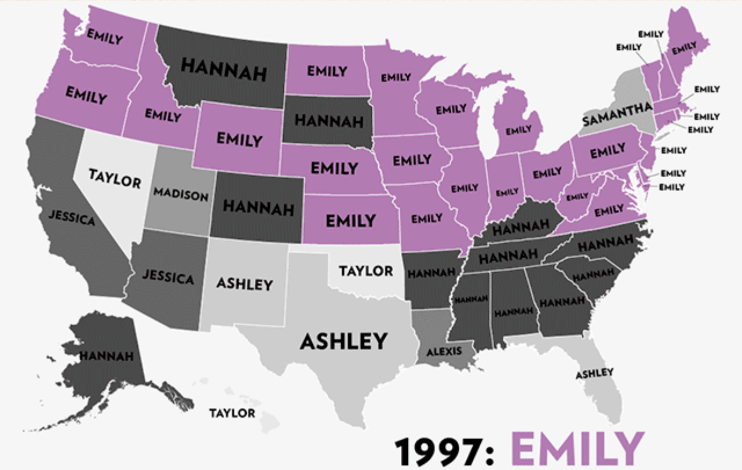


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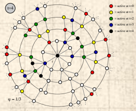

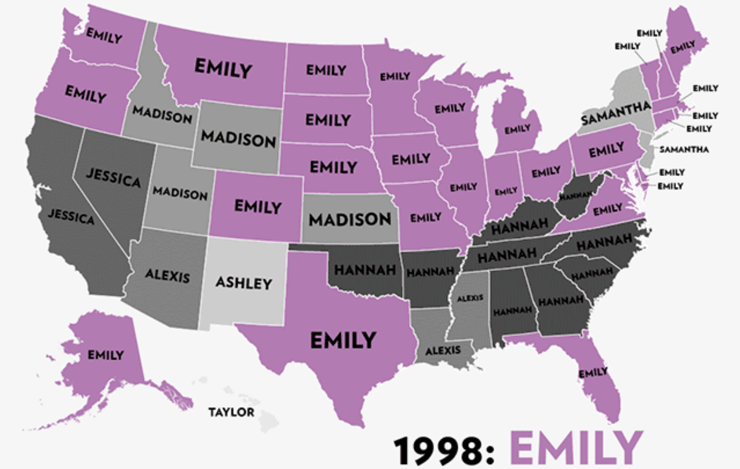


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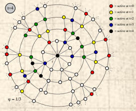

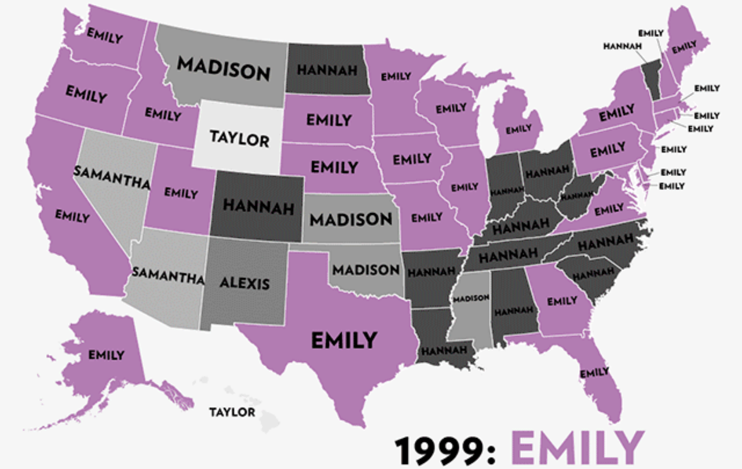


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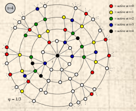

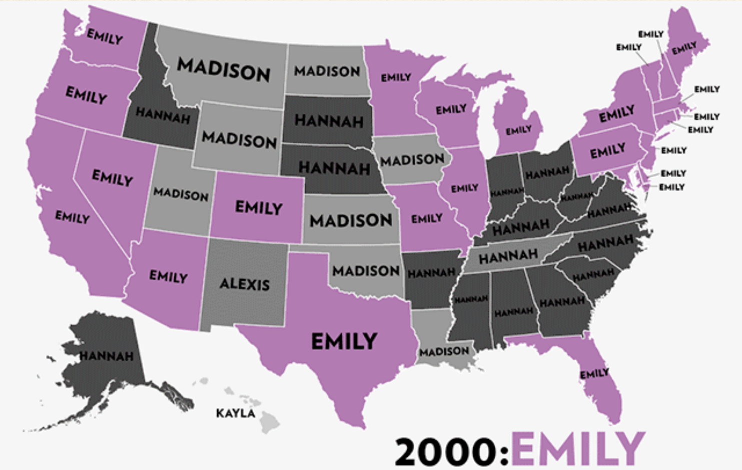


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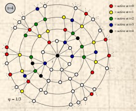

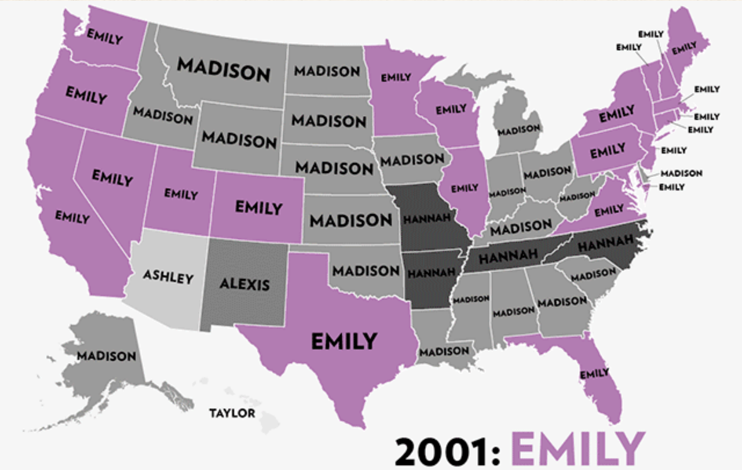


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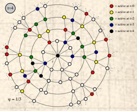

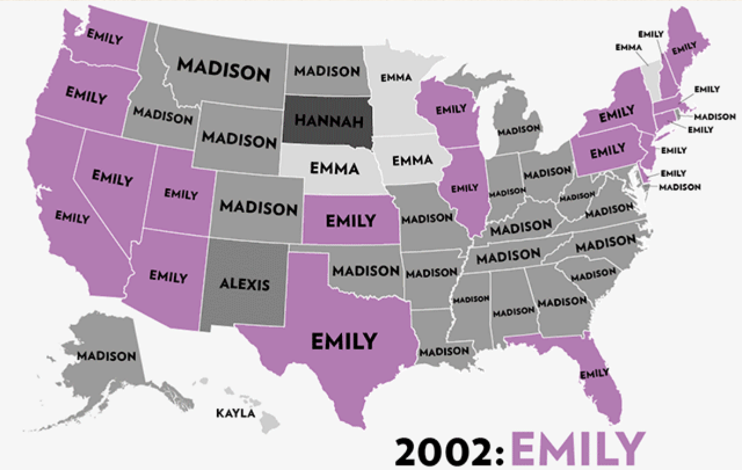


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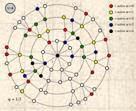

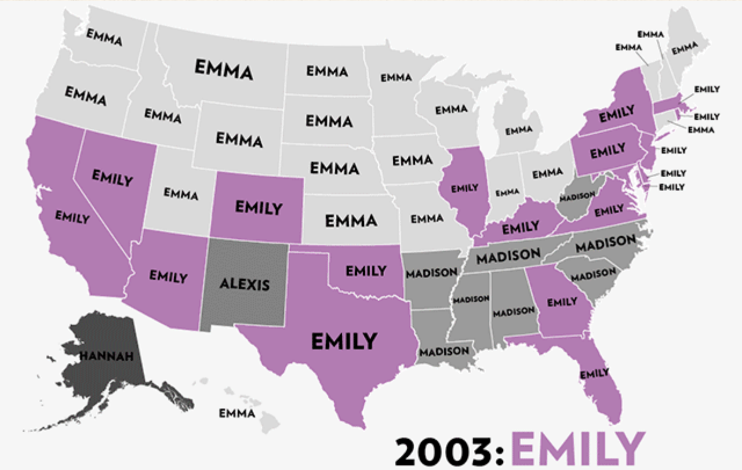


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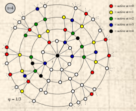

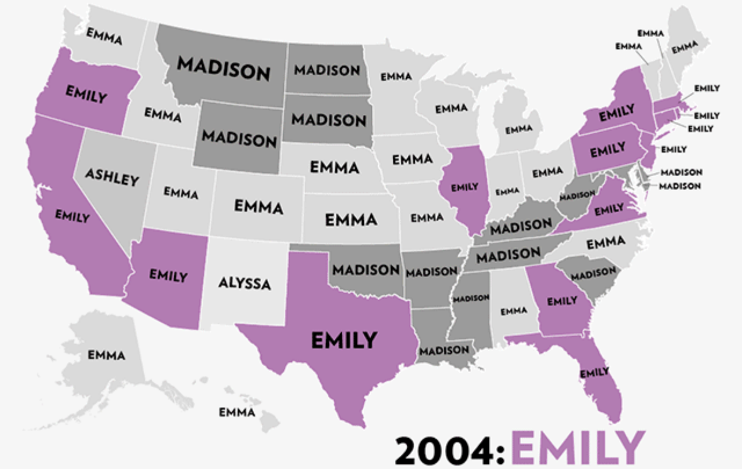


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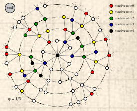

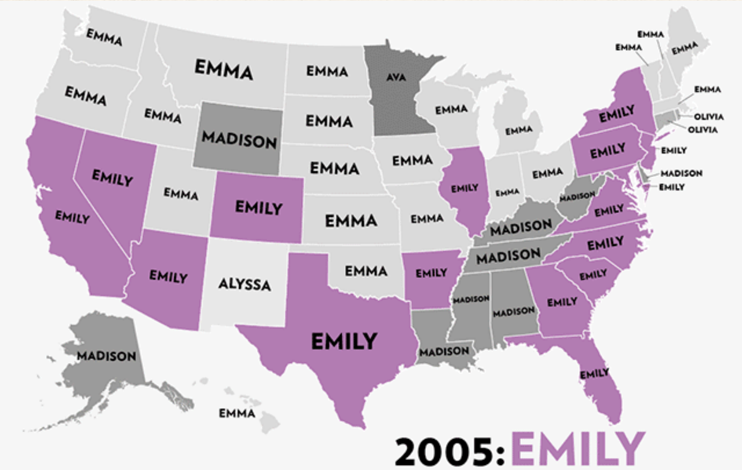


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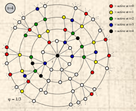

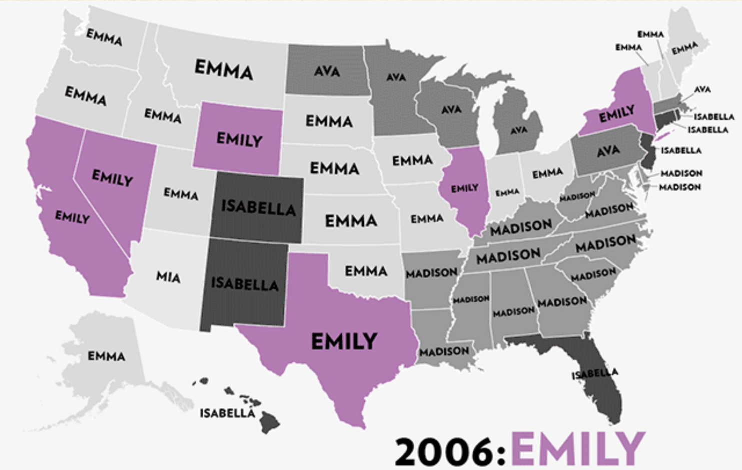


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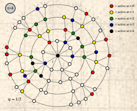

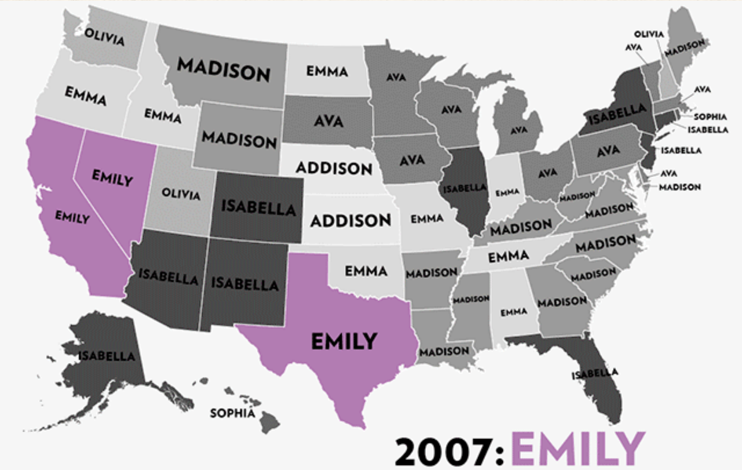


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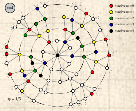

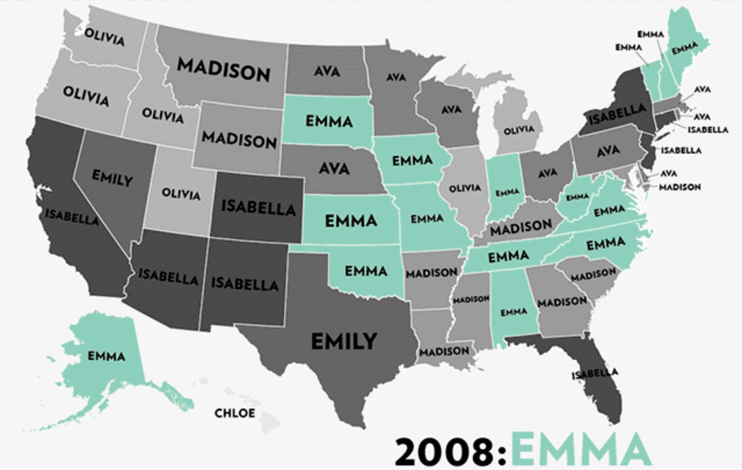


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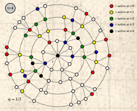
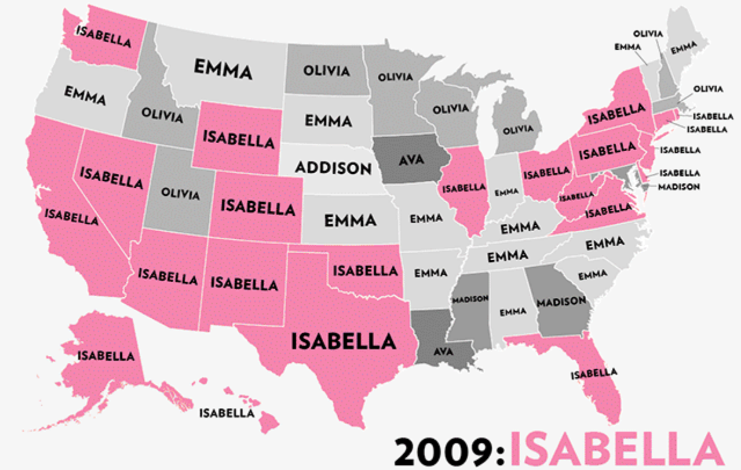
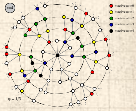
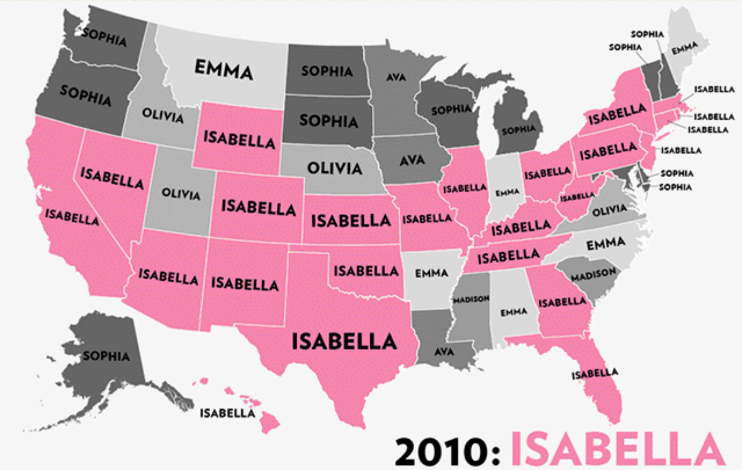





[From the Atlantic](#)



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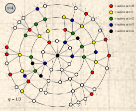

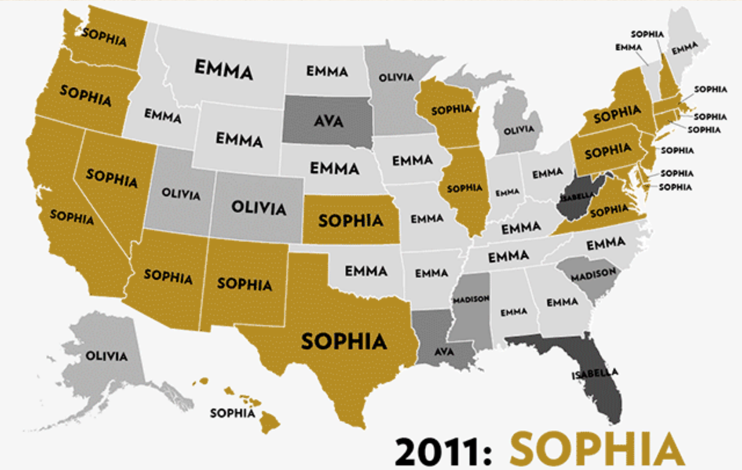


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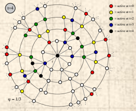

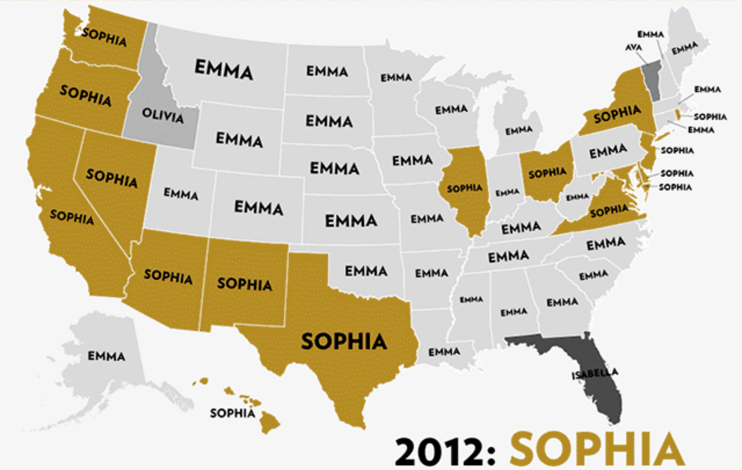


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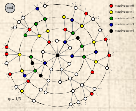
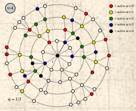
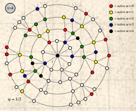


# Richard Feynmann on the Social Sciences:



# Sheldon Cooper on the Social Sciences:



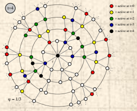
# Things that spread well:





buzzfeed.com:


- Dangerously self aware: 11 Elements that make a perfect viral video.



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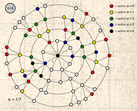
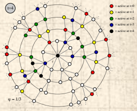
# + News ...



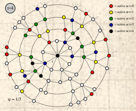
# LOL + cute + fail + wtf:

# The whole lolcats thing:



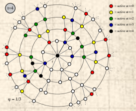


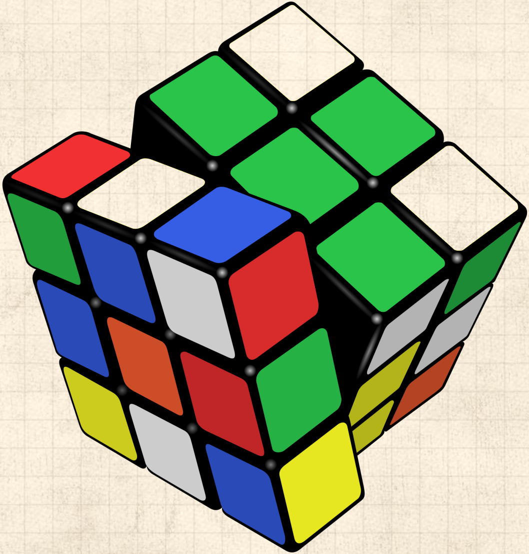
# Some things really stick:





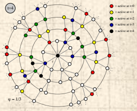


# wtf + geeky + omg:







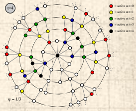


# Outline

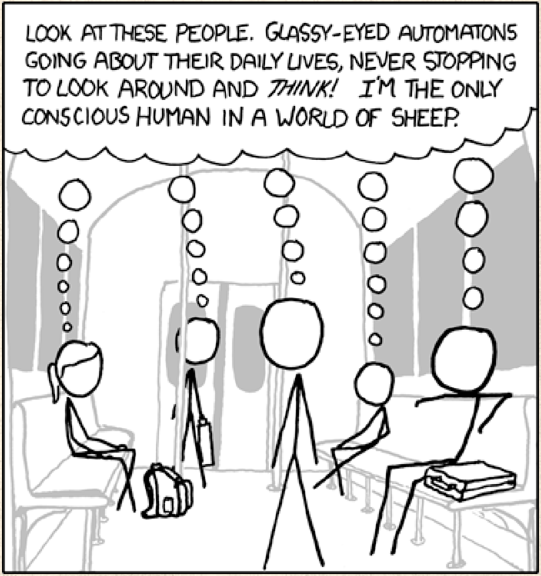








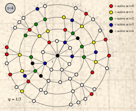
# Why social contagion works so well:




http://xkcd.com/610/



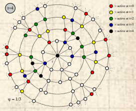




# Social Contagion





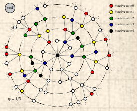


# Social Contagion

## Examples are claimed to abound:

- Fashion
- Striking
- smoking [7]
- Residential segregation [23]
- iPhones and iThings
- obesity [6]
- Stupidity
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- school shootings





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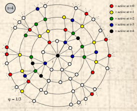

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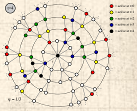

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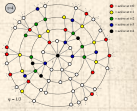
## SIR and SIRS type contagion possible

- Classes of behavior versus specific behavior



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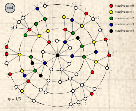


## SIR and SIRS type contagion possible

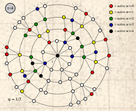
- Classes of behavior versus specific behavior : dieting, horror movies, getting married, invading countries, ...

# Mixed messages: Please copy, but also, don't copy ...

http://www.youtube.com/watch?v=TgDxWNV4wWY?rel=0







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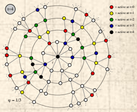

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- Cindy Harrell appeared in the (terrifying) music video for Ray Parker Jr.'s Ghostbusters.

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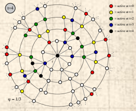
- In Stranger Things 2, Steve Harrington reveals his Fabergé secret.

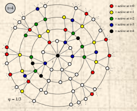




# Market much?

http://www.youtube.com/watch?v=FEaCfIp9qR4?rel=0

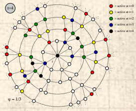
- Advertisement enjoyed during "Herstory of Dance", Community S4E08, April 2013.



# Framingham heart study:

## Evolving network stories (Christakis and Fowler):

- The spread of quitting smoking [7]
- The spread of spreading [6]



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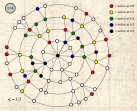

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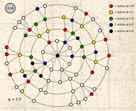

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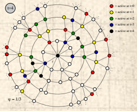
## Controversy:

- Are your friends making you fat? (Clive Thomspon, NY Times, September 10, 2009).



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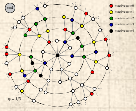
- Everything is contagious—Doubts about the social plague stir in the human superorganism (Dave Johns, Slate, April 8, 2010).





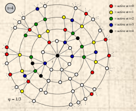


# Social Contagion

## Two focuses for us







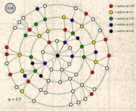
# Social Contagion





## Two focuses for us

- Widespread media influence



# Social Contagion





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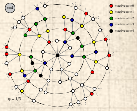


# Social Contagion

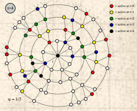




## Two focuses for us

- Widespread media influence
- Word-of-mouth influence

## We need to understand influence



# Social Contagion





## Two focuses for us

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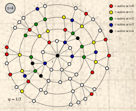
## We need to understand influence

- Who influences whom?



# Social Contagion





## Two focuses for us

- Widespread media influence
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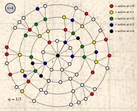
- Who influences whom? Very hard to measure...



# Social Contagion





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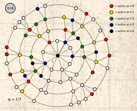
- Who influences whom? Very hard to measure...
- What kinds of influence response functions are there?



# Social Contagion





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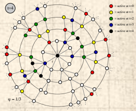

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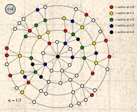

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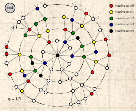
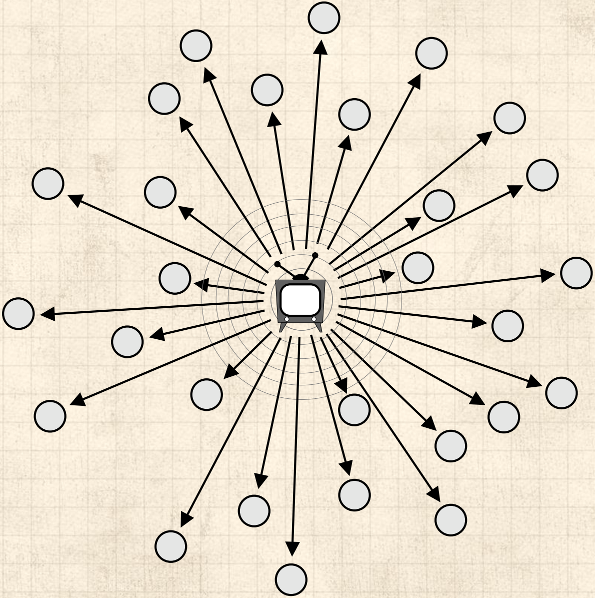
- The infectious idea of opinion leaders (Katz and Lazarsfeld) [19]

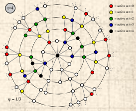


# The hypodermic model of influence





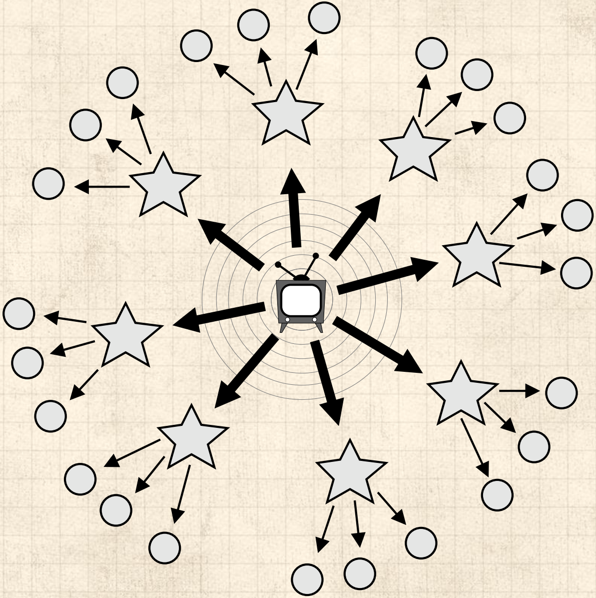


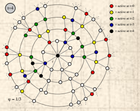


# The two step model of influence [19]

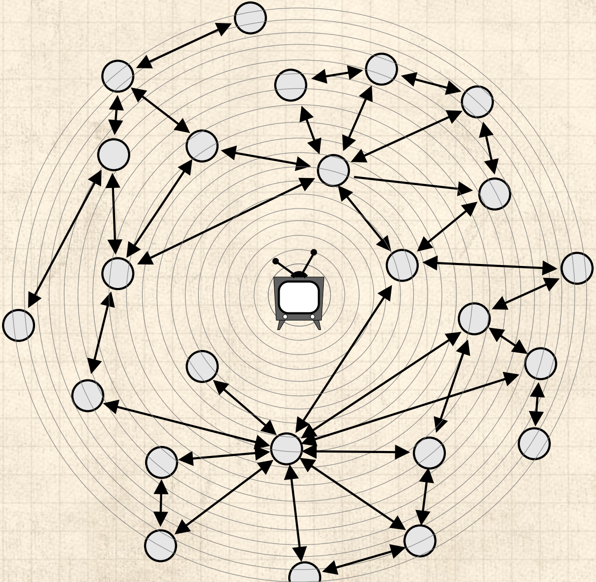




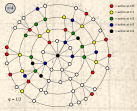




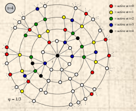
# The general model of influence: the Social Wild







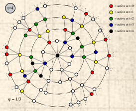
# Talking about the social wild:



# Why do things spread socially?







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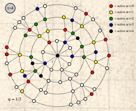
- Because of properties of special individuals?





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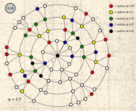
- Because of properties of special individuals?
- Or system level properties?



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- Because of properties of special individuals?
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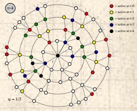
- Is the match that lights the fire important?







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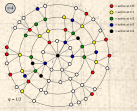

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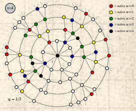
- We like to think things happened for reasons ...







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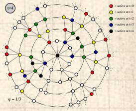

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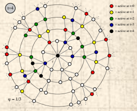

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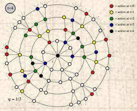

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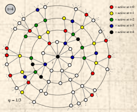
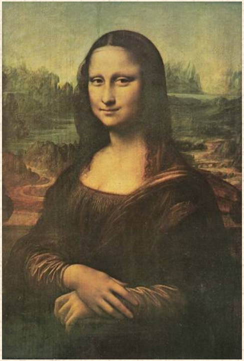


# The Mona Lisa



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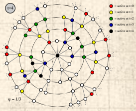

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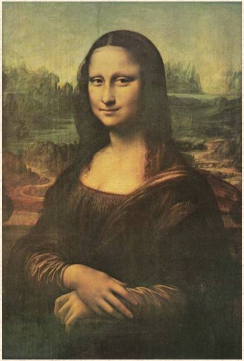

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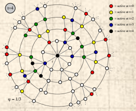

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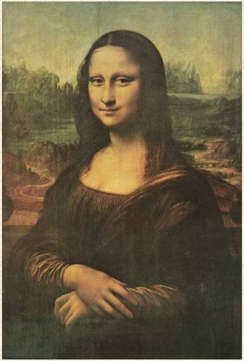

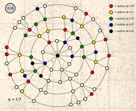

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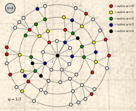

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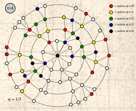

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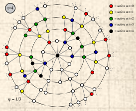

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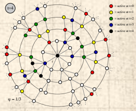
# 'Tattooed Guy' Was Pivotal in Armstrong Case [nytimes]


"... Leogrande's doping sparked a series of events ..."



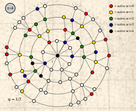




# The completely unpredicted fall of Eastern Europe:

Timunr Kuran: [20, 21] “Now Out of Never: The Element of Surprise in the East European Revolution of 1989”

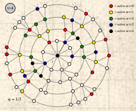




# The dismal predictive powers of editors...





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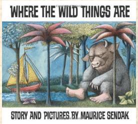

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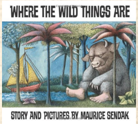

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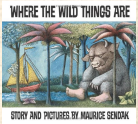

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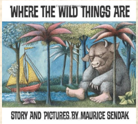

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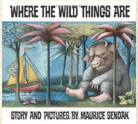

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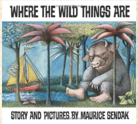

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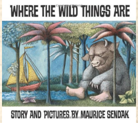

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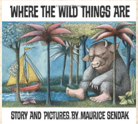

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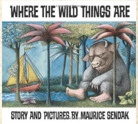

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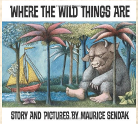

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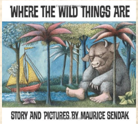

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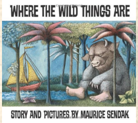

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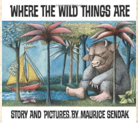


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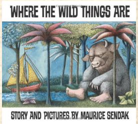

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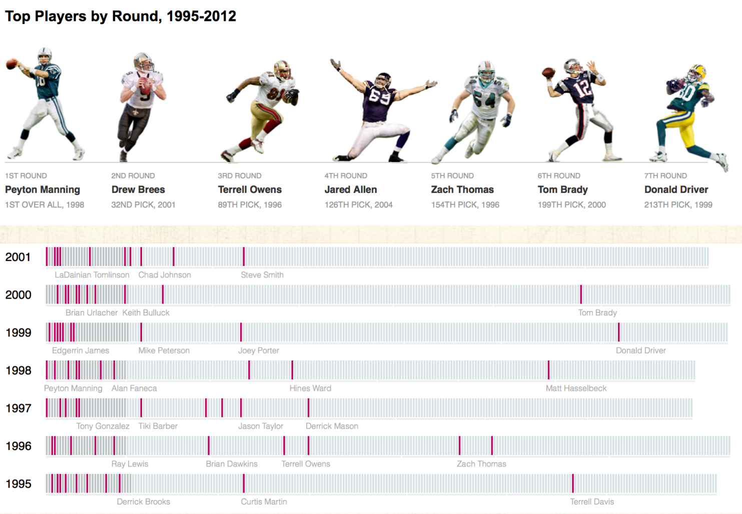
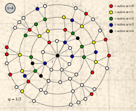



# Social Contagion

## Messing with social connections







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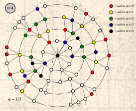

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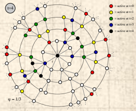

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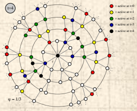

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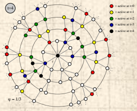

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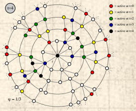

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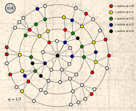

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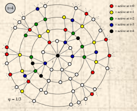
A very good book: 'Influence' [8] by Robert Cialdini





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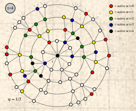

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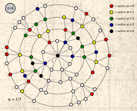

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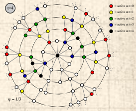

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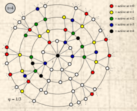

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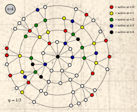

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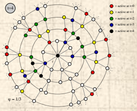

# Getting others to do things for you

A very good book: 'Influence'[8] by Robert Cialdini

Six modes of influence:

1. Reciprocation: *The Old Give and Take... and Take*; e.g., Free samples, Hare Krishnas.
2. Commitment and Consistency: *Hobgoblins of the Mind*; e.g., Hazing.
3. Social Proof: *Truths Are Us*; e.g., Jonestown, Kitty Genovese (contested).
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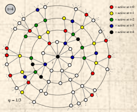
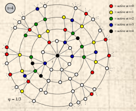
6. Scarcity: *The Rule of the Few*; e.g., Prohibition.



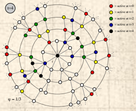
# Social proof:



# Social contagion





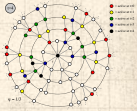


# Social contagion

- Cialdini's modes are heuristics that help up us get through life.







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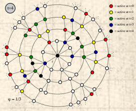

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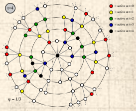
Other acts of influence:



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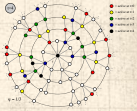

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- Conspicuous Consumption (Veblen, 1912)
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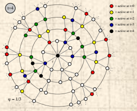


THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
THE WELL OF SCALES
THE LAWS OF DECAYING POWER
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MINISTRY OF RANDOM WALKS
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THE LAW OF DIGITS FIRST
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THE MANY TALES OF MANY TAILS
THE MEASURING
THE DATA POOR
THE POURING DATA
THE CHARMS OF THE MANY WRONG PATHS
THE DOORS THAT SHOULD NOT BE OPENED
THE KNOWLEDGE OF DEAD MONKS
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THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
THE ARKS OF THE RANDOM NETWORK
THE STRANGENESS OF FRIENDS
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
THE CONTAGION
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE SOCIAL WILD
THE SOCIAL CONTAGION
THE RATIO OF GAIN
THE MECHANICS OF FAME
THE TALK OF FAME
THE STORIES CONTAGIOUS
THE JOHN DORY
THE ADJACENT NARRATIVES
THE STORYTELLERS
THE FATED ASTRAL PATH
THE PATHS OF UNIVERSALITY
THE DEPENDENT PATHS
THE TROUSERS OF BIFURCATING REALITIES
THE UNKNOWN MECHANISM
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THE ILL-SCALING OF ALLOMETRIC BODIES
THE SUPPLY MOST FAIR
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THE DARK ART OF GENERATING FUNCTIONS
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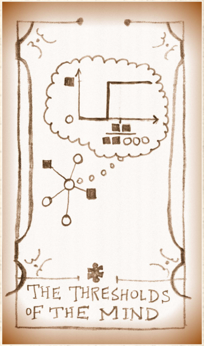
THE END


THE THRESHOLDS OF THE MIND

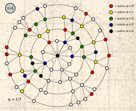
# Social Contagion

## Some important models:

- Tipping models—Schelling (1971) [23, 24, 25]







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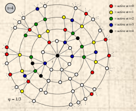

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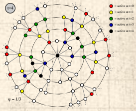

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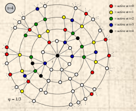

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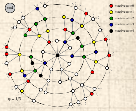

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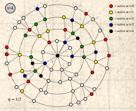

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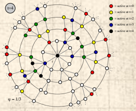
  - Social learning theory, Informational cascades,...

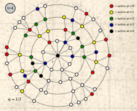


# Social contagion models

## Thresholds







# Social contagion models





## Thresholds

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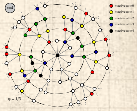

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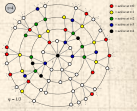

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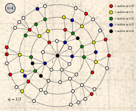

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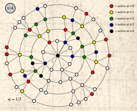

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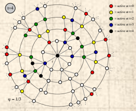

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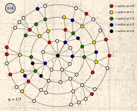

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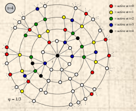

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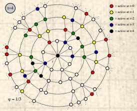

# Social Contagion





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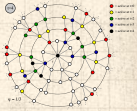

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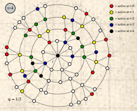

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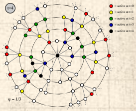

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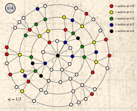

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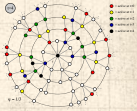

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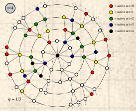

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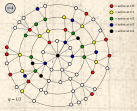
  - Examples: telephones, fax machine, Facebook, operating systems
  - An individual's utility increases with the adoption level among peers and the population in general

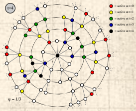


# Outline



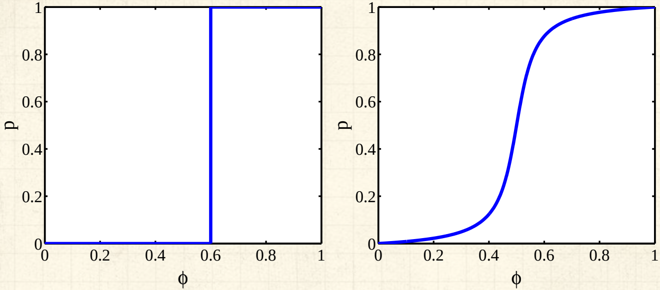




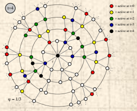


# Threshold models—response functions






- Example threshold influence response functions: deterministic and stochastic



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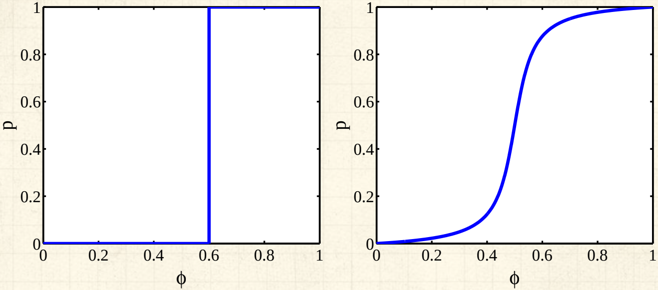


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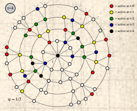

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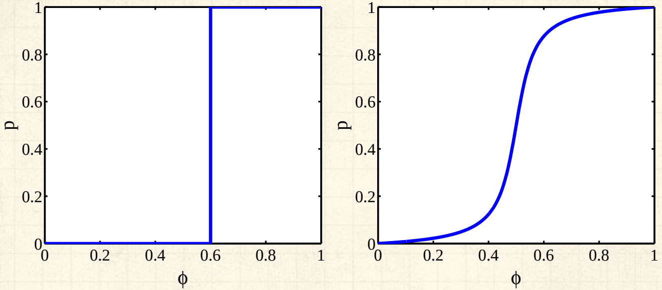


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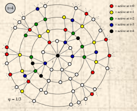

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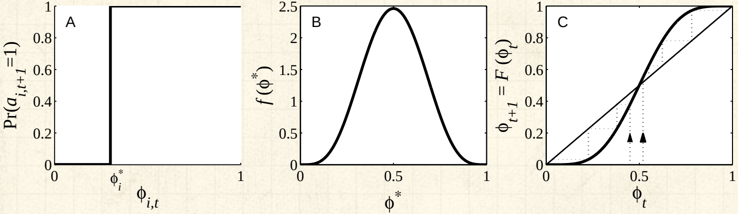
## Action based on perceived behavior of others:

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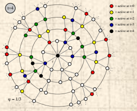

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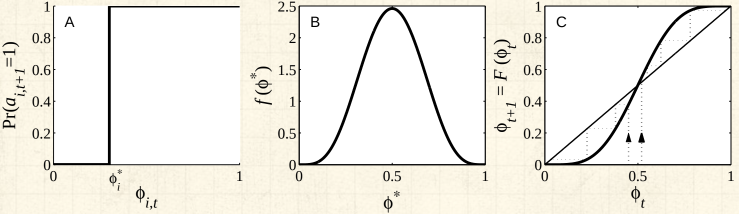


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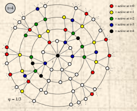
- Discrete time update (strong assumption!)



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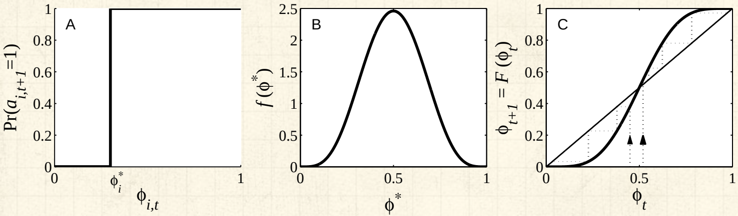


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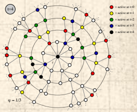
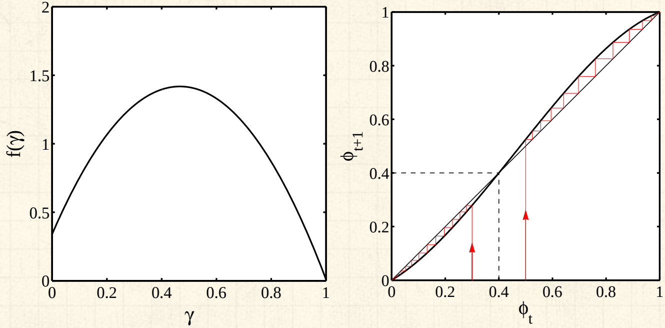
- This is a Critical mass model

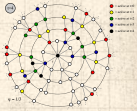


# Threshold models



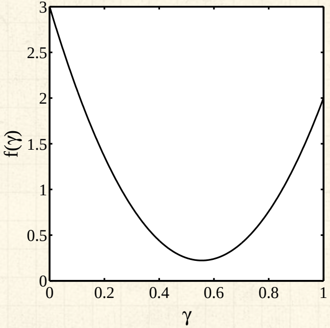
## Another example of critical mass model:

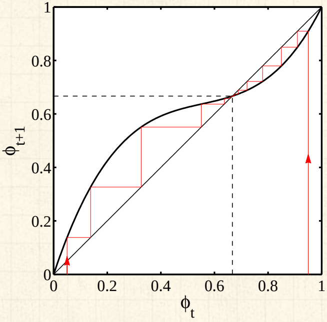


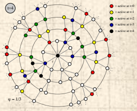



# Threshold models

## Example of single stable state model:



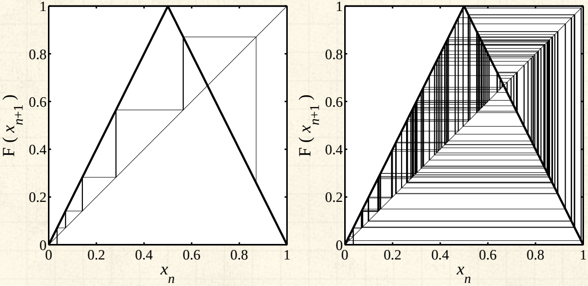



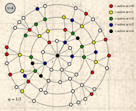
# Threshold models





## Chaotic behavior possible [17, 16, 9, 18]



# Threshold models





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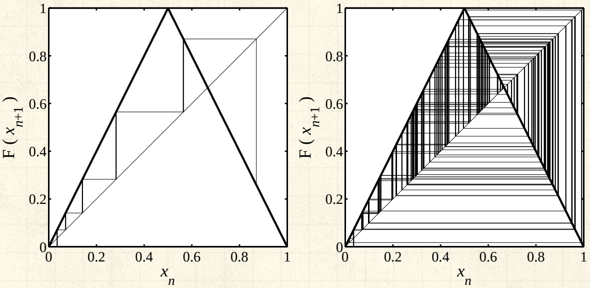
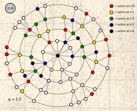



- Period doubling arises as map amplitude $r$ is increased.



# Threshold models





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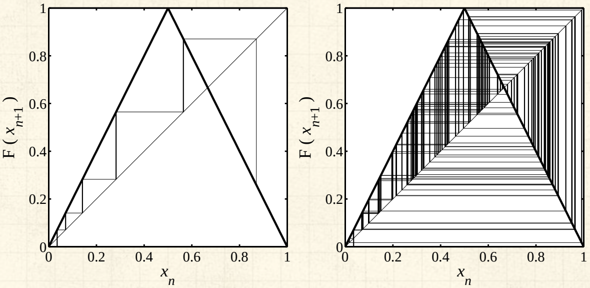
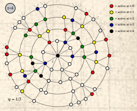



- Period doubling arises as map amplitude $r$ is increased.
- Synchronous update assumption is crucial

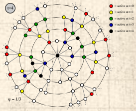


# Threshold models—Nutshell





## Implications for collective action theory:



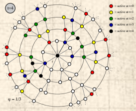
# Threshold models—Nutshell





Implications for collective action theory:

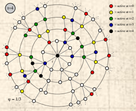
1. Collective uniformity $\nRightarrow$ individual uniformity



# Threshold models—Nutshell

Implications for collective action theory:

1. Collective uniformity $\nRightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes

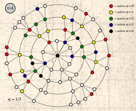


# Threshold models—Nutshell



## Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes
3. The stories/dynamics of complex systems are conceptually inaccessible for individual-centric narratives.



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Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
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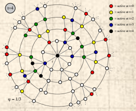
4. System stories live in left null space of our stories—we can't even see them.

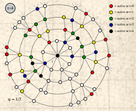


# Threshold models—Nutshell



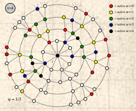
Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes
3. The stories/dynamics of complex systems are conceptually inaccessible for individual-centric narratives.
4. System stories live in left null space of our stories—we can't even see them.
5. But we happily impose simplistic, individual-centric stories—we can't help ourselves.



# Outline



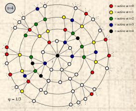


# Many years after Granovetter and Soong's work:

- "A simple model of global cascades on random networks"
  D. J. Watts. Proc. Natl. Acad. Sci., 2002 [27]







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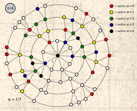
  - Mean field model $\rightarrow$ network model







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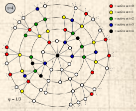

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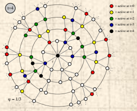
## We'll also explore:

- "Seed size strongly affects cascades on random networks" [14]
  Gleeson and Cahalane, Phys. Rev. E, 2007.
- "Direct, phyiscally motivated derivation of the contagion condition for spreading processes on generalized random networks" [10] Dodds, Harris, and Payne, Phys. Rev. E, 2011
- "Influentials, Networks, and Public Opinion Formation" [28]
  Watts and Dodds, J. Cons. Res., 2007.



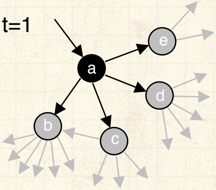




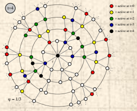
# Threshold model on a network








- All nodes have threshold $\phi = 0.2$.



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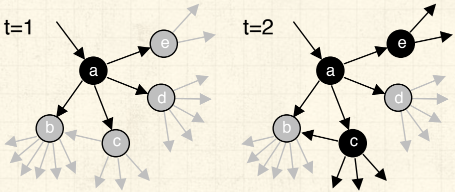


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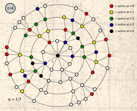

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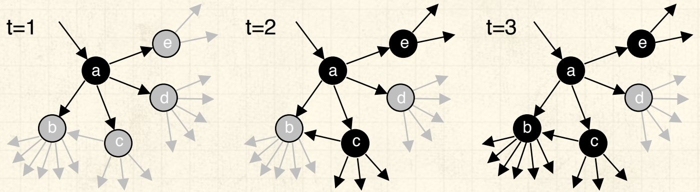


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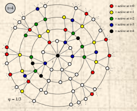
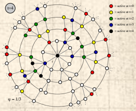


# Threshold model on a network





- Interactions between individuals now represented by a network.

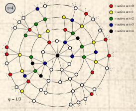


# Threshold model on a network

- Interactions between individuals now represented by a network.
- Network is sparse.





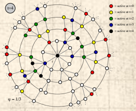


# Threshold model on a network

- Interactions between individuals now represented by a network.
- Network is sparse.
- Individual $i$ has $k_i$ contacts.







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- Interactions between individuals now represented by a network.
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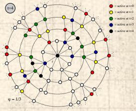

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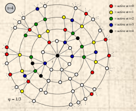

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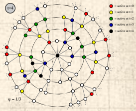
- Individuals repeatedly poll contacts on network.







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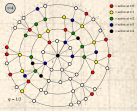

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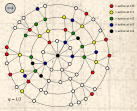

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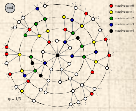
- Individuals remain active when switched (no recovery = SI model).

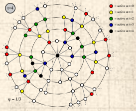


# Snowballing

First study random networks:







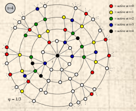
# Snowballing





## First study random networks:

- Start with $N$ nodes with a degree distribution $P_k$



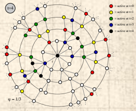
# Snowballing





## First study random networks:

- Start with $N$ nodes with a degree distribution $P_k$
- Nodes are randomly connected (carefully so)



# Snowballing

## First study random networks:

- Start with $N$ nodes with a degree distribution $P_k$
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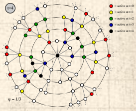
- Aim: Figure out when activation will propagate



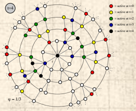
# Snowballing





## First study random networks:

- Start with $N$ nodes with a degree distribution $P_k$
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition



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## First study random networks:

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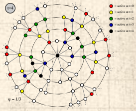
## The Cascade Condition:

1. If one individual is initially activated, what is the probability that an activation will spread over a network?



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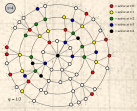
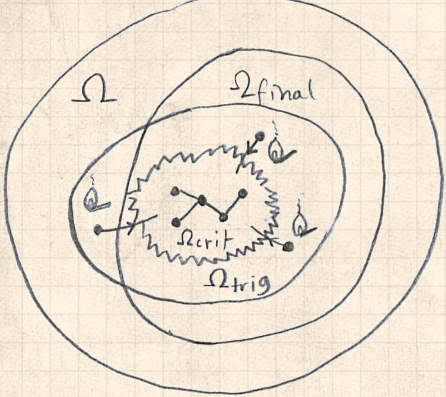
- Start with $N$ nodes with a degree distribution $P_k$
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

## The Cascade Condition:

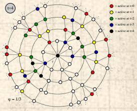
1. If one individual is initially activated, what is the probability that an activation will spread over a network?
2. What features of a network determine whether a cascade will occur or not?



# Example random network structure:




- $\Omega_{\rm crit} = \Omega_{\rm vuln} =$ critical mass = global vulnerable component
- $\Omega_{\rm trig} =$ triggering component
- $\Omega_{\rm final} =$ potential extent of spread
- $\Omega =$ entire network



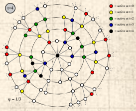
$\Omega_{\rm crit} \subset \Omega_{\rm trig};\ \Omega_{\rm crit} \subset \Omega_{\rm final};$ and $\Omega_{\rm trig}, \Omega_{\rm final} \subset \Omega.$

# Snowballing





## Follow active links



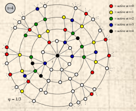
# Snowballing





## Follow active links

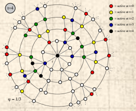
- An active link is a link connected to an activated node.



# Snowballing

## Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.



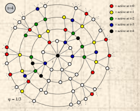
# Snowballing





## Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.
- We need to understand which nodes can be activated when only one of their neigbors becomes active.

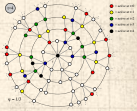


# The most gullible





## Vulnerables:

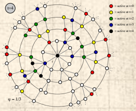


# The most gullible



## Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables



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## Vulnerables:

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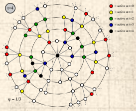
- The vulnerability condition for node $i$:

$$1/k_i \geq \phi_i$$





# The most gullible

## Vulnerables:

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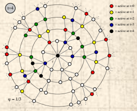
- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$





# The most gullible





## Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node $i$:

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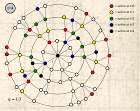
- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [27]



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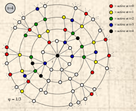

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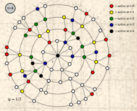
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

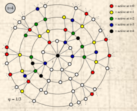


# Cascade condition





Back to following a link:



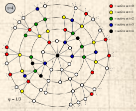
# Cascade condition





## Back to following a link:

- A randomly chosen link, traversed in a random direction, leads to a degree $k$ node with probability $\propto kP_k$.



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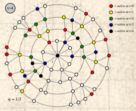

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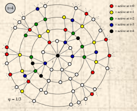
$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle$$



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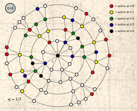
- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$





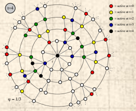


# Cascade condition

Next: Vulnerability of linked node







# Cascade condition

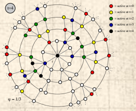




## Next: Vulnerability of linked node

- Linked node is vulnerable with probability

$$\beta_k = \int_{\phi'_*=0}^{1/k} f(\phi'_*) \mathrm{d}\phi'_*$$



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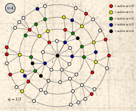

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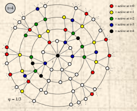
- If linked node is vulnerable, it produces $k-1$ new outgoing active links
- If linked node is not vulnerable, it produces no active links.



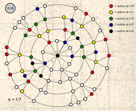
# Cascade condition





## Putting things together:

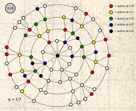
- Expected number of active edges produced by an active edge:



# Cascade condition







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- Expected number of active edges produced by an active edge:

$$R = \left[ \underbrace{\sum_{k=1}^{\infty} (k-1) \cdot \beta_k \cdot \frac{kP_k}{\langle k \rangle}}_{\text{success}} + \right]$$

# Cascade condition

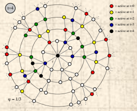




## Putting things together:

- Expected number of active edges produced by an active edge:

$$R = \left[ \underbrace{\sum_{k=1}^{\infty} (k-1) \cdot \beta_k \cdot \frac{kP_k}{\langle k \rangle}}_{\text{success}} + \underbrace{0 \cdot (1-\beta_k) \cdot \frac{kP_k}{\langle k \rangle}}_{\text{failure}} \right]$$



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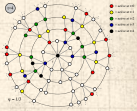
$$= \sum_{k=1}^{\infty} (k-1) \cdot \beta_k \cdot \frac{kP_k}{\langle k \rangle}$$



# Cascade condition

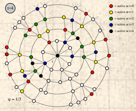




So... for random networks with fixed degree distributions, cacades take off when:

$$\sum_{k=1}^{\infty}(k-1)\cdot\beta_k\cdot\frac{kP_k}{\langle k\rangle}>1.$$

- $\beta_k =$ probability a degree $k$ node is vulnerable.
- $P_k =$ probability a node has degree $k$.

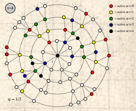


# Cascade condition





Two special cases:



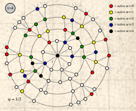
# Cascade condition





## Two special cases:

- (1) Simple disease-like spreading succeeds: $\beta_{\boldsymbol{k}} = \beta$



# Cascade condition



## Two special cases:

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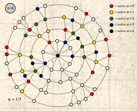
$$\beta \cdot \sum_{k=1}^{\infty} (k-1) \cdot \frac{kP_k}{\langle k \rangle} > 1.$$



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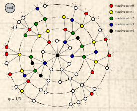

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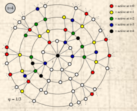
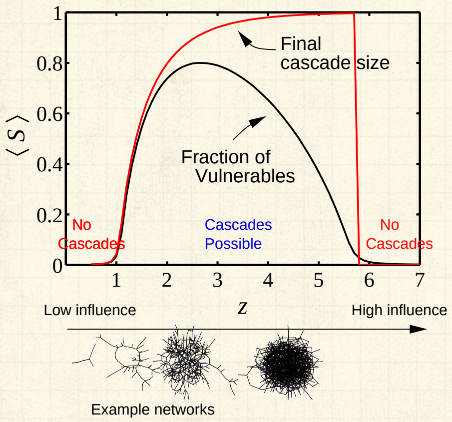


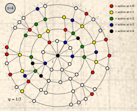
# Cascades on random networks



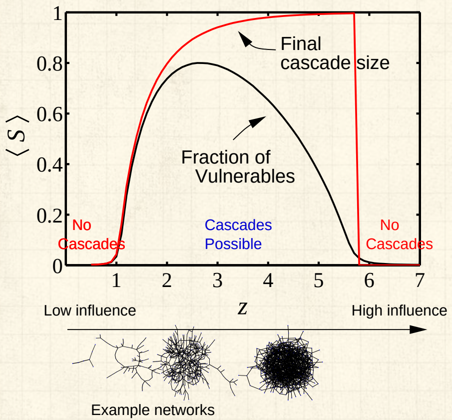





- Cascades occur only if size of max vulnerable cluster $> 0$.

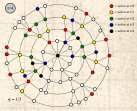


# Cascades on random networks




- Cascades occur only if size of max vulnerable cluster $> 0$.
- System may be 'robust-yet-fragile'.

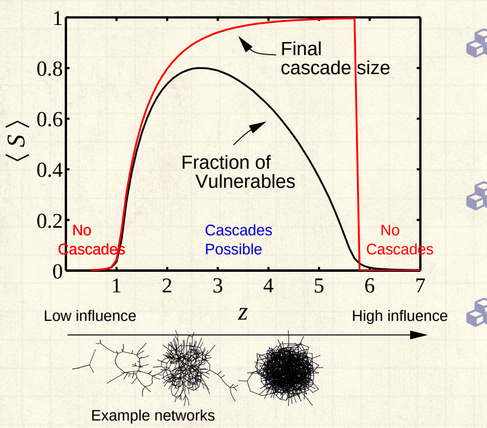




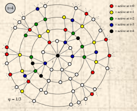
# Cascades on random networks



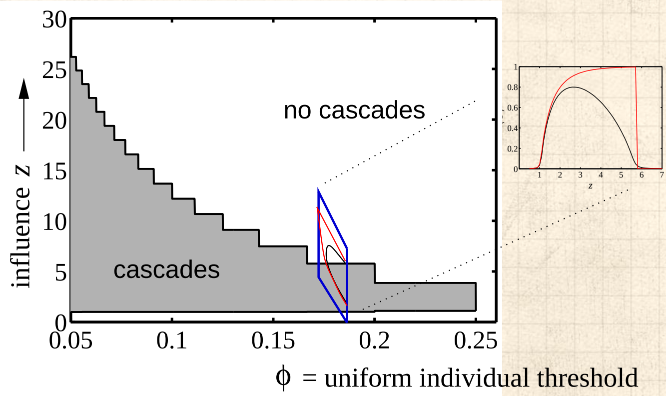




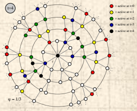

- Cascades occur only if size of max vulnerable cluster $> 0$.
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.



# Cascade window for random networks




- 'Cascade window' widens as threshold $\phi$ decreases.
- Lower thresholds enable spreading.



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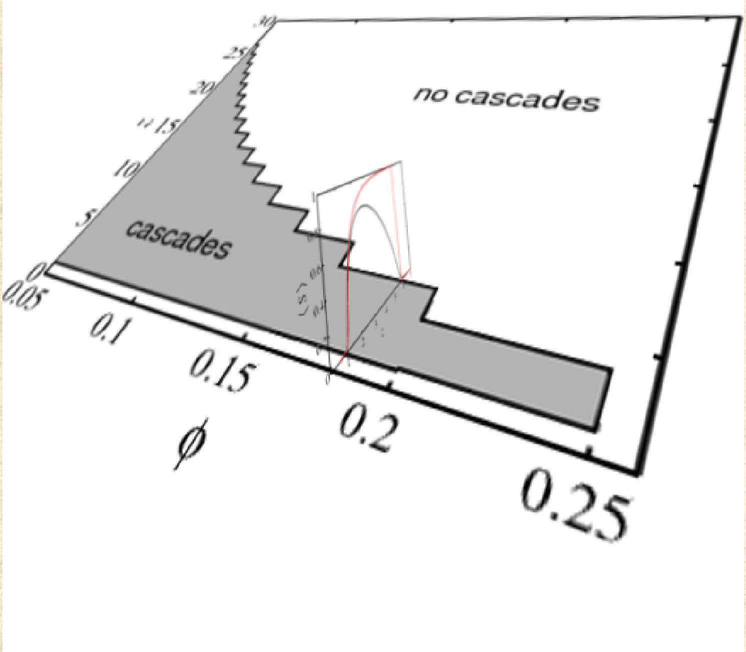
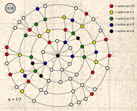
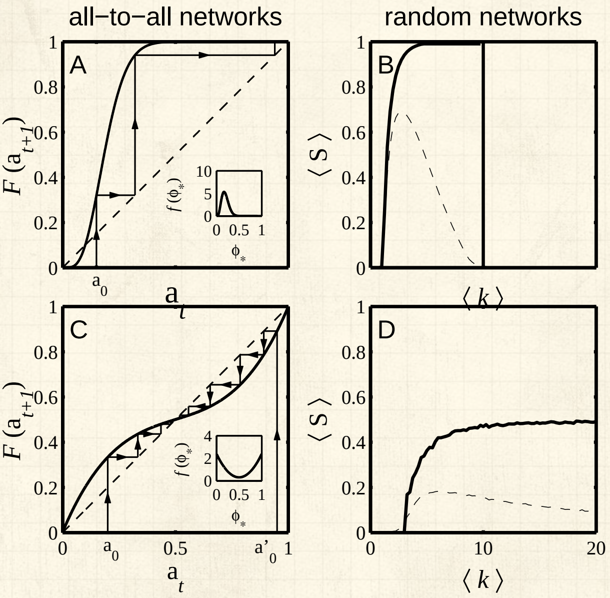


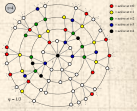



# All-to-all versus random networks







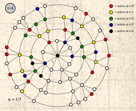



# Cascade window—summary

For our simple model of a uniform threshold:







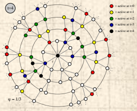
# Cascade window—summary





For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks.
   No global clusters of any kind.



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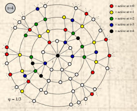

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For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks.
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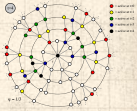
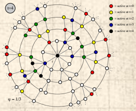
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists.
   Cascades are possible in "Cascade window."



# Outline



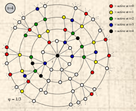


# Threshold contagion on random networks





- **Next:** Find expected fractional size of spread.

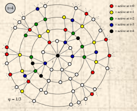


# Threshold contagion on random networks

- **Next:** Find expected fractional size of spread.
- Not obvious even for uniform threshold problem.





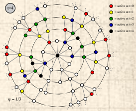


# Threshold contagion on random networks





- Next: Find expected fractional size of spread.
- Not obvious even for uniform threshold problem.
- Difficulty is in figuring out if and when nodes that need $\geq 2$ hits switch on.



# Threshold contagion on random networks

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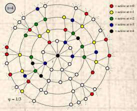

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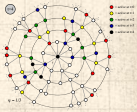
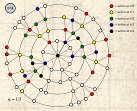
- Developed further by Gleeson in "Cascades on correlated and modular random networks," Phys. Rev. E, 2008. [13]



# Determining expected size of spread:

- Randomly turn on a fraction $\phi_0$ of nodes at time $t = 0$



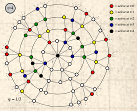


# Determining expected size of spread:

- Randomly turn on a fraction $\phi_0$ of nodes at time $t = 0$
- Capitalize on local branching network structure of random networks (again)

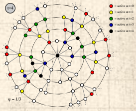






# Determining expected size of spread:

- Randomly turn on a fraction $\phi_0$ of nodes at time $t = 0$
- Capitalize on local branching network structure of random networks (again)
- Now think about what must happen for a specific node $i$ to become active at time $t$:



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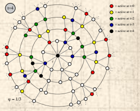
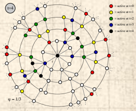


# Determining expected size of spread:





- Randomly turn on a fraction $\phi_0$ of nodes at time $t = 0$
- Capitalize on local branching network structure of random networks (again)
- Now think about what must happen for a specific node $i$ to become active at time $t$:
  - $t = 0$: $i$ is one of the seeds (prob = $\phi_0$)
  - $t = 1$: $i$ was not a seed but enough of $i$'s friends switched on at time $t = 0$ so that $i$'s threshold is now exceeded.



# Determining expected size of spread:

- Randomly turn on a fraction $\phi_0$ of nodes at time $t = 0$
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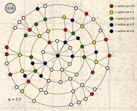

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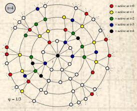
  - $t = n$: enough nodes within $n$ hops of $i$ switched on at $t = 0$ and their effects have propagated to reach $i$.



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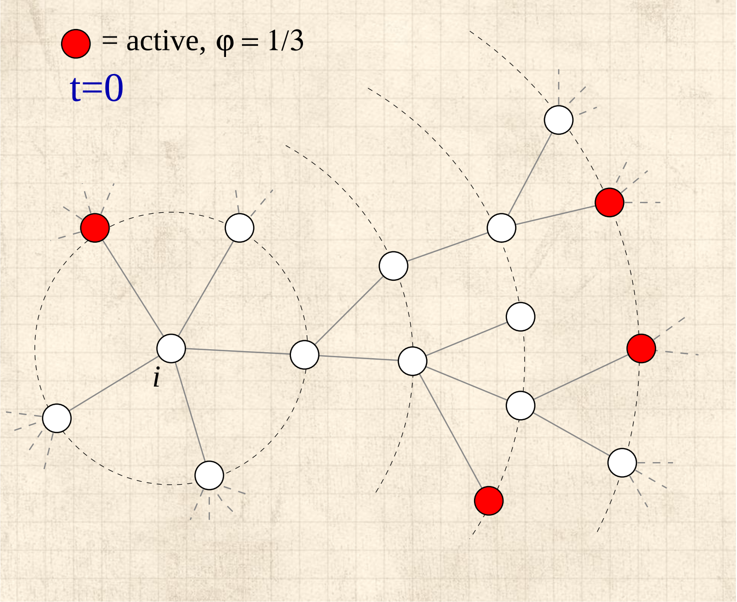


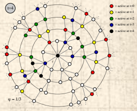

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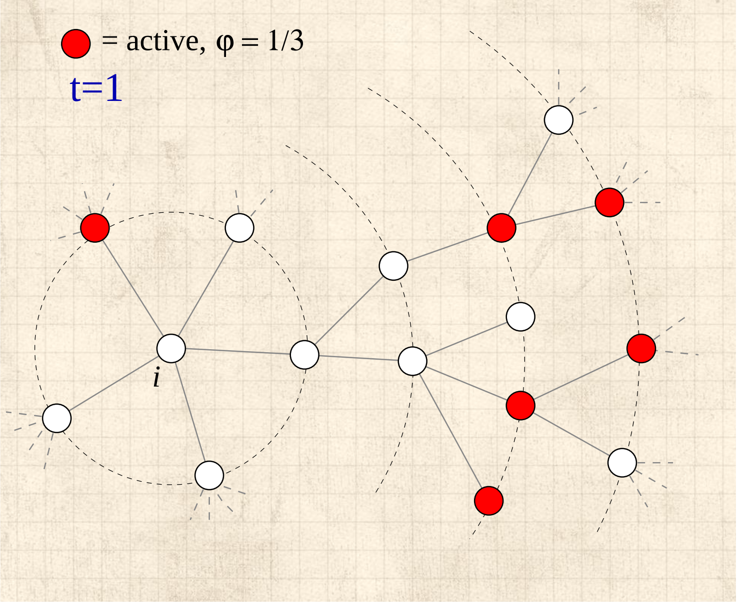


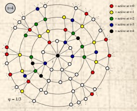

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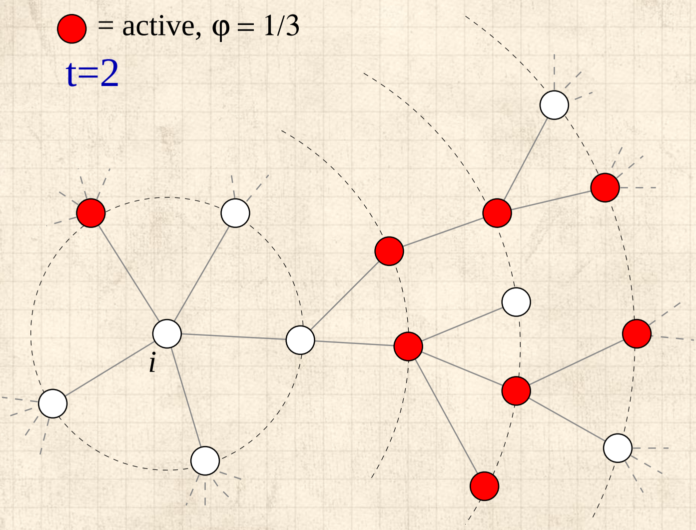


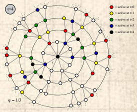

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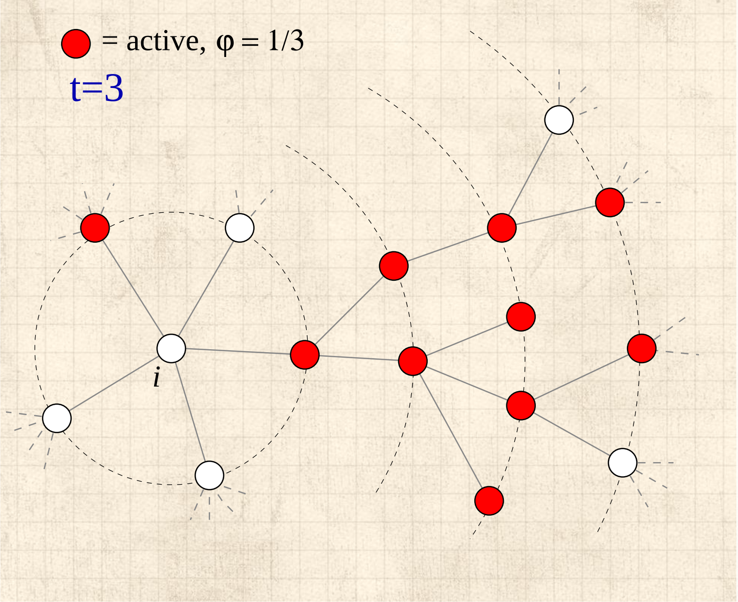






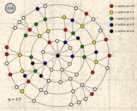

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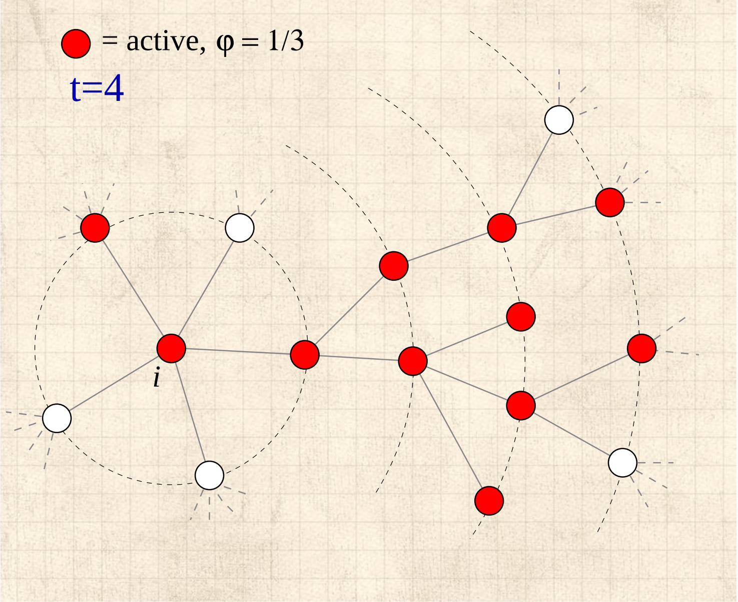




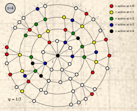

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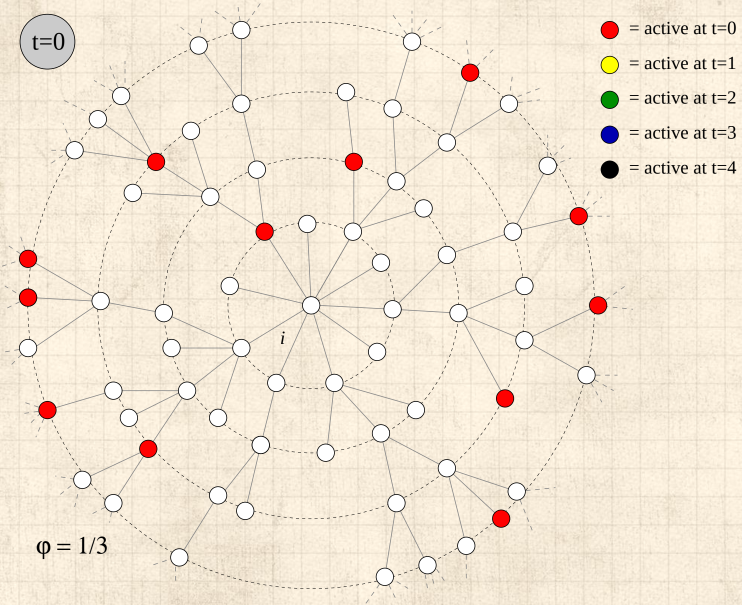


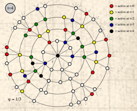

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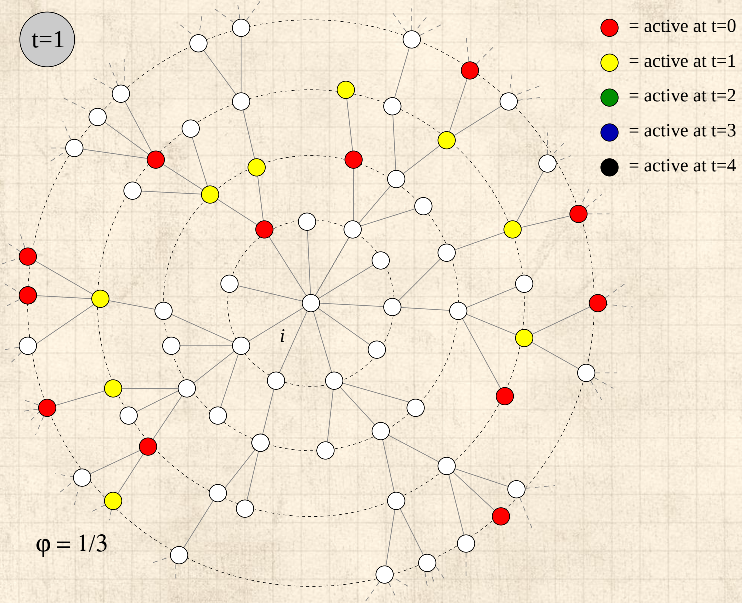


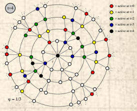

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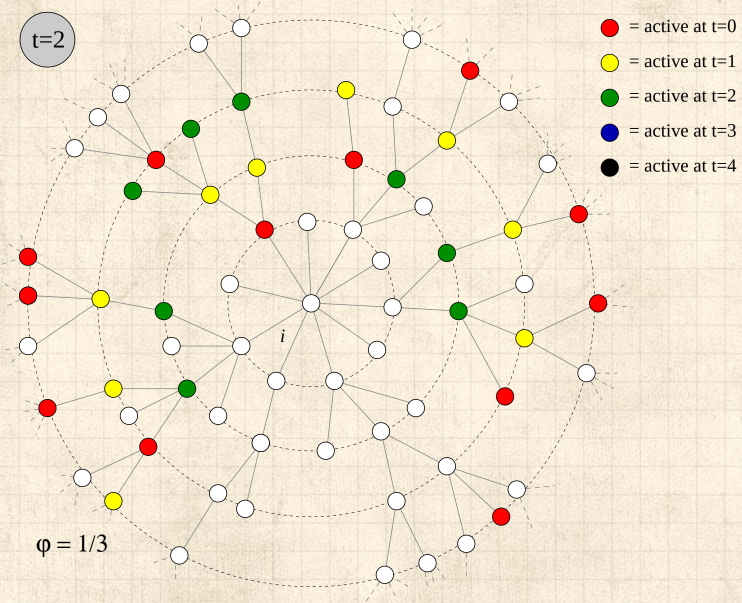


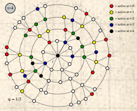

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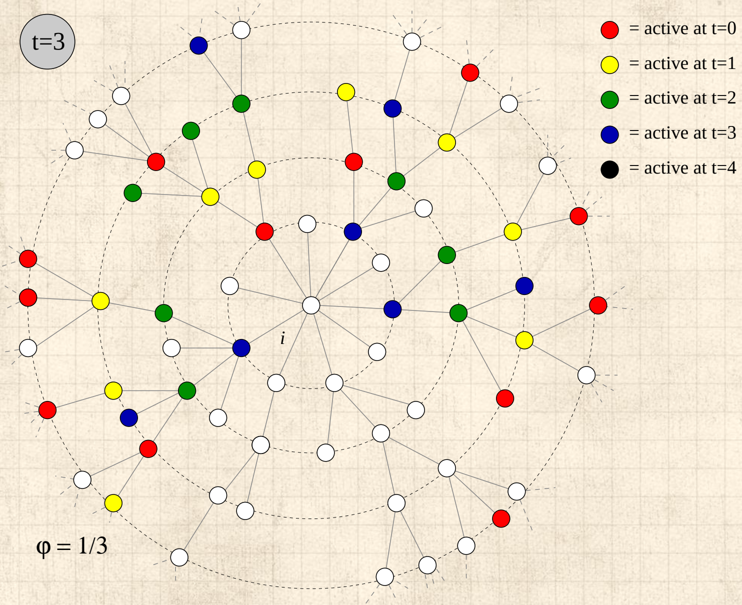


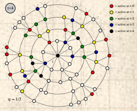

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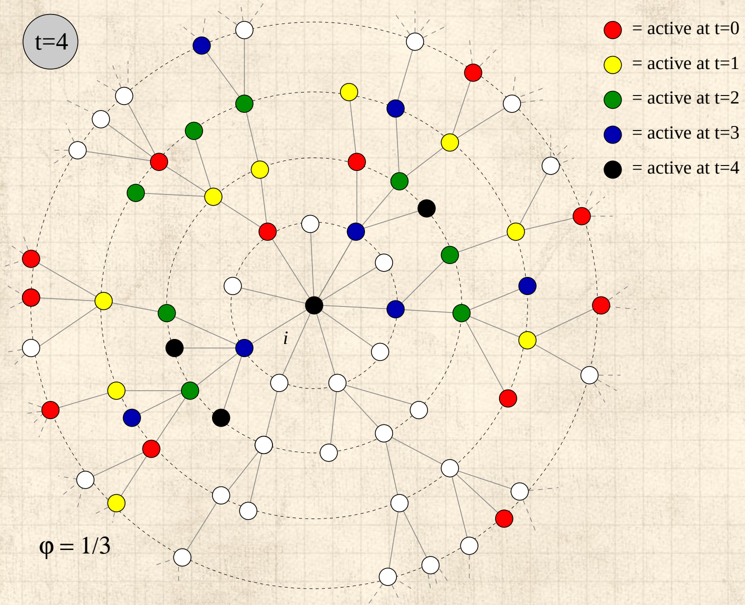




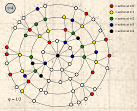

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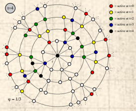

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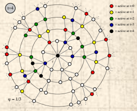

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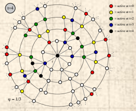

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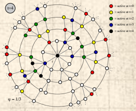

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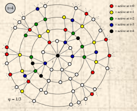


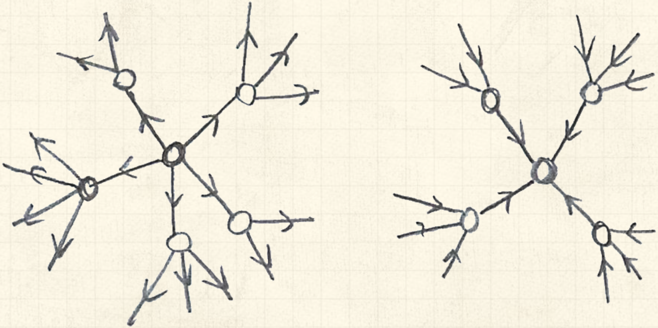
# Expected size of spread

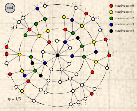




## Pleasantness:

- Taking off from a single seed story is about expansion away from a node.





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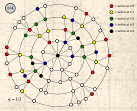

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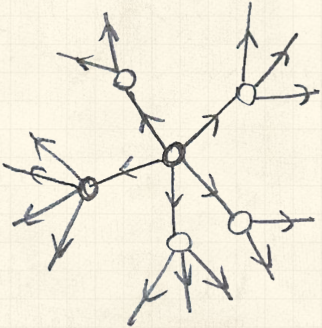

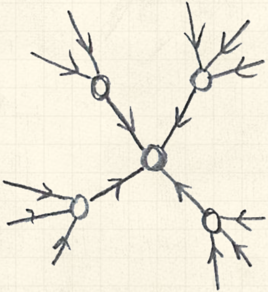

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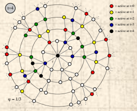
  $\phi_{k,t} = \mathbf{Pr}$(a degree $k$ node is active at time $t$).







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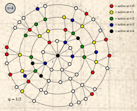

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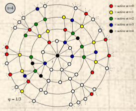

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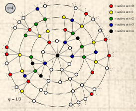

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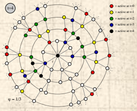

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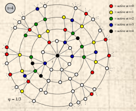

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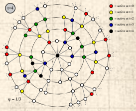
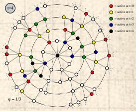
- Probability a degree $k$ node was a seed at $t = 0$ is $\phi_0$ (as above).
- Probability a degree $k$ node was not a seed at $t = 0$ is $(1-\phi_0)$.
- Combining everything, we have:

$$\phi_{k,1} = \phi_0 + (1-\phi_0)\sum_{j=0}^{k}\binom{k}{j}\phi_0^j(1-\phi_0)^{k-j}B_{kj}.$$



- For general $t$, we need to know the probability an edge coming into a degree $k$ node at time $t$ is active.



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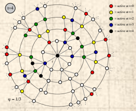

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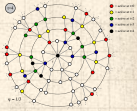

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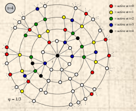
$$\phi_{i,t+1} = \phi_0 + (1-\phi_0) \sum_{j=0}^{k_i} \binom{k_i}{j} \theta_t^j (1-\theta_t)^{k_i - j} B_{k_i j}.$$



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- Average over all nodes to obtain expression for $\phi_{t+1}$:

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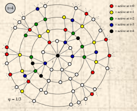

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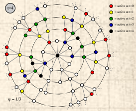

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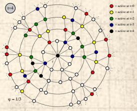


# Expected size of spread



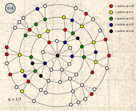


## First connect $\theta_0$ to $\theta_1$:

- $\theta_1 = \phi_0 +$

$$(1-\phi_0)\sum_{k=1}^{\infty}\frac{kP_k}{\langle k\rangle}\sum_{j=0}^{k-1}\binom{k-1}{j}\theta_0^{\,j}(1-\theta_0)^{k-1-j}B_{kj}$$

- $\frac{kP_k}{\langle k\rangle} = R_k$ = **Pr** (edge connects to a degree $k$ node).
- $\sum_{j=0}^{k-1}$ piece gives **Pr**(degree node $k$ activates) of its neighbors $k-1$ incoming neighbors are active.
- $\phi_0$ and $(1-\phi_0)$ terms account for state of node at time $t=0$.



# Expected size of spread

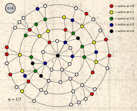


## First connect $\theta_0$ to $\theta_1$:

- $\theta_1 = \phi_0 +$

$$(1-\phi_0) \sum_{k=1}^{\infty} \frac{k P_k}{\langle k \rangle} \sum_{j=0}^{k-1} \binom{k-1}{j} \theta_0^{\,j} (1-\theta_0)^{k-1-j} B_{kj}$$

- $\frac{k P_k}{\langle k \rangle} = R_k$ = **Pr** (edge connects to a degree $k$ node).
- $\sum_{j=0}^{k-1}$ piece gives **Pr**(degree node $k$ activates) of its neighbors $k-1$ incoming neighbors are active.
- $\phi_0$ and $(1-\phi_0)$ terms account for state of node at time $t=0$.
- See this all generalizes to give $\theta_{t+1}$ in terms of $\theta_t$...



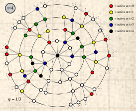
# Expected size of spread

## Two pieces: edges first, and then nodes

1. $$\theta_{t+1} = \underbrace{\phi_0}_{\text{exogenous}} + (1-\phi_0)\underbrace{\sum_{k=1}^{\infty}\frac{kP_k}{\langle k\rangle}\sum_{j=0}^{k-1}\binom{k-1}{j}\theta_t^{\,j}(1-\theta_t)^{k-1-j}B_{kj}}_{\text{social effects}}$$

   with $\theta_0 = \phi_0$.

2. $$\phi_{t+1} = \underbrace{\phi_0}_{\text{exogenous}} + (1-\phi_0)\underbrace{\sum_{k=0}^{\infty}P_k\sum_{j=0}^{k}\binom{k}{j}\theta_t^{\,j}(1-\theta_t)^{k-j}B_{kj}}_{\text{social effects}}.$$



# Expected size of spread

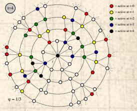


Iterative map for $\theta_t$ is key:

$$\theta_{t+1} = \underbrace{\phi_0}_{\text{exogenous}}$$

$$+(1-\phi_0)\underbrace{\sum_{k=1}^{\infty}\frac{kP_k}{\langle k\rangle}\sum_{j=0}^{k-1}\binom{k-1}{j}\theta_t^{\,j}(1-\theta_t)^{k-1-j}B_{kj}}_{\text{social effects}}$$

$$= G(\theta_t;\phi_0)$$

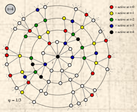


# Expected size of spread:

- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \to 0$.





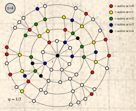


# Expected size of spread:

- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \to 0$.
- Depends on map $\theta_{t+1} = G(\theta_t; \phi_0)$.







# Expected size of spread:

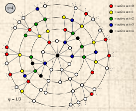




- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \to 0$.
- Depends on map $\theta_{t+1} = G(\theta_t; \phi_0)$.
- First: if self-starters are present, some activation is assured:

$$G(0; \phi_0) = \sum_{k=1}^{\infty} \frac{kP_k}{\langle k \rangle} \bullet B_{k0} > 0.$$

meaning $B_{k0} > 0$ for at least one value of $k \geq 1$.



# Expected size of spread:





- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \rightarrow 0$.
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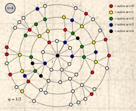
  meaning $B_{k0} > 0$ for at least one value of $k \geq 1$.
- If $\theta = 0$ is a fixed point of $G$ (i.e., $G(0;\phi_0) = 0$) then spreading occurs if

$$G'(0;\phi_0) = \sum_{k=0}^{\infty} \frac{kP_k}{\langle k \rangle} \bullet (k-1) \bullet B_{k1} > 1.$$

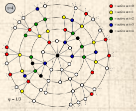


# Expected size of spread:

## In words:

- If $G(0;\phi_0) > 0$, spreading must occur because some nodes turn on for free.





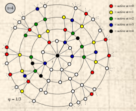
# Expected size of spread:





## In words:

- If $G(0;\phi_0) > 0$, spreading must occur because some nodes turn on for free.
- If $G$ has an unstable fixed point at $\theta = 0$, then cascades are also always possible.



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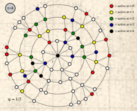
## Non-vanishing seed case:

- Cascade condition is more complicated for $\phi_0 > 0$.



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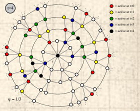
## Non-vanishing seed case:

- Cascade condition is more complicated for $\phi_0 > 0$.
- If $G$ has a stable fixed point at $\theta = 0$, and an unstable fixed point for some $0 < \theta_* < 1$, then for $\theta_0 > \theta_*$, spreading takes off.



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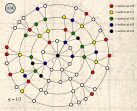
- Tricky point: $G$ depends on $\phi_0$, so as we change $\phi_0$, we also change $G$.



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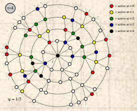
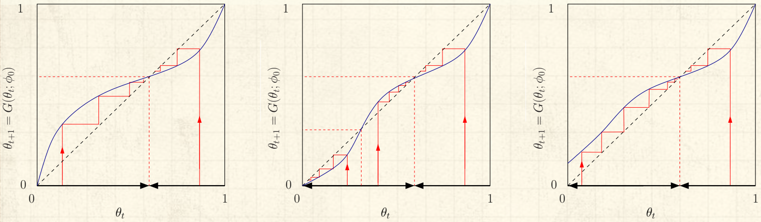
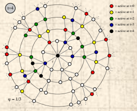
- Tricky point: $G$ depends on $\phi_0$, so as we change $\phi_0$, we also change $G$.
- A version of a critical mass model again.



# General fixed point story:




- Given $\theta_0 (= \phi_0)$, $\theta_\infty$ will be the nearest stable fixed point, either above or below.



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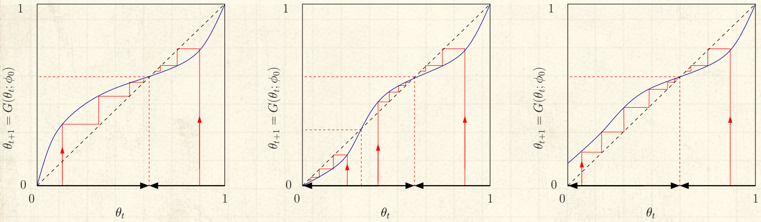
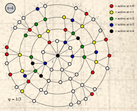



- Given $\theta_0 (= \phi_0)$, $\theta_\infty$ will be the nearest stable fixed point, either above or below.
- n.b., adjacent fixed points must have opposite stability types.



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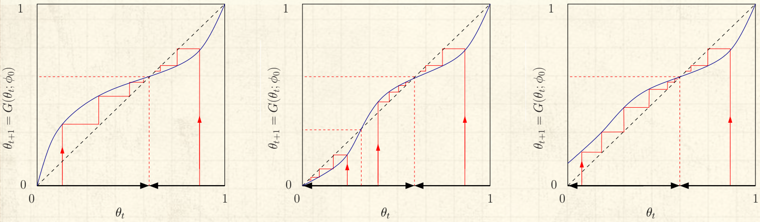


- Given $\theta_0 (= \phi_0)$, $\theta_\infty$ will be the nearest stable fixed point, either above or below.
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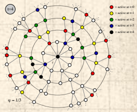
- Important: Actual form of $G$ depends on $\phi_0$.



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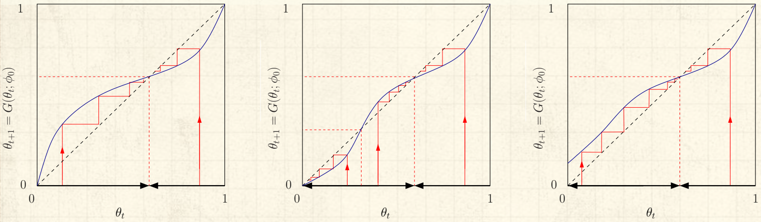
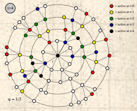


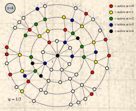

- Given $\theta_0 (= \phi_0)$, $\theta_\infty$ will be the nearest stable fixed point, either above or below.
- n.b., adjacent fixed points must have opposite stability types.
- Important: Actual form of $G$ depends on $\phi_0$.
- So choice of $\phi_0$ dictates both $G$ and starting point—can't start anywhere for a given $G$.



# Outline

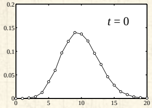






# Early adopters—degree distributions

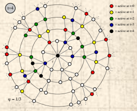
$t = 0$




$P_{k,t}$ versus $k$

Unpublished?



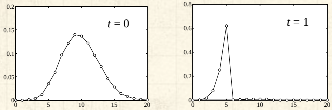


# Early adopters—degree distributions



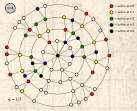


$t = 0$ $t = 1$




$P_{k,t}$ versus $k$

Unpublished?



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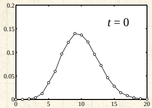
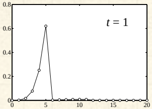
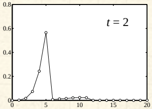



$t = 1$



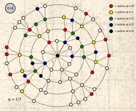

$t = 2$




$P_{k,t}$ versus $k$

Unpublished?





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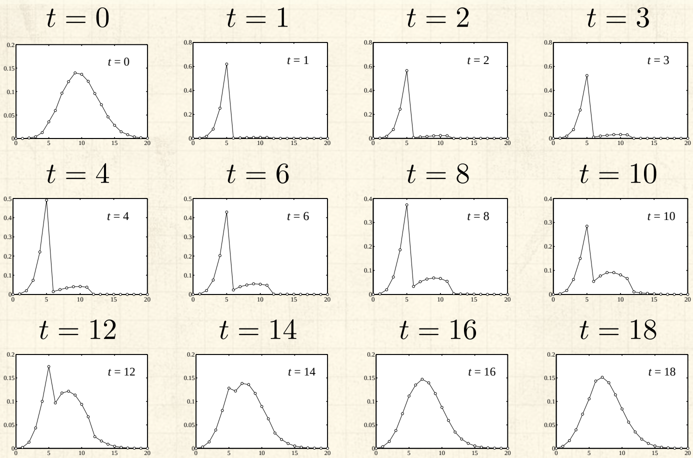


$P_{k,t}$ versus $k$

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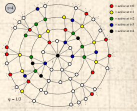
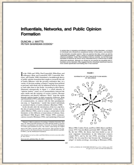
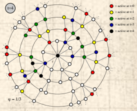



Influentials, Networks, and Public Opinion Formation
DUNCAN J. WATTS
PETER SHERIDAN DODDS*

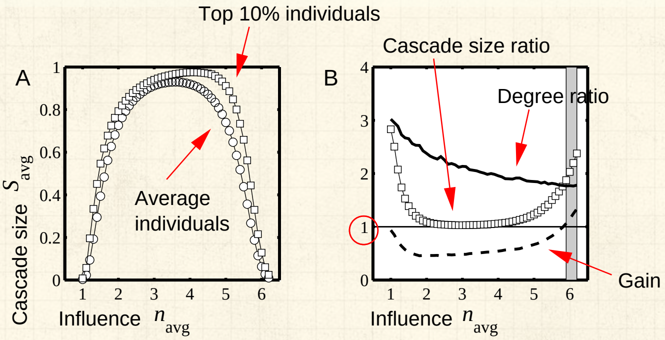
"Influentials, Networks, and Public Opinion Formation"
Watts and Dodds,
J. Consum. Res., **34**, 441–458, 2007. [28]

- Exploration of threshold model of social contagion on various networks.
- "Influentials" are limited in power.
- Connected groups of weakly influential-vulnerable" individuals are key.
- Average individuals can have more power than well connected ones.

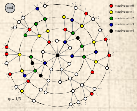


# The multiplier effect:






- Fairly uniform levels of individual influence.
- Multiplier effect is mostly below 1.



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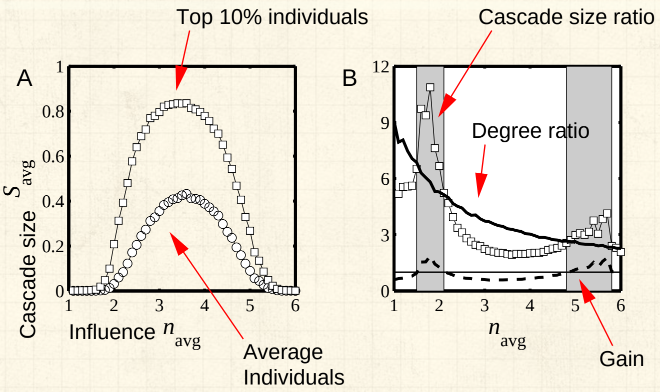
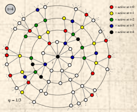


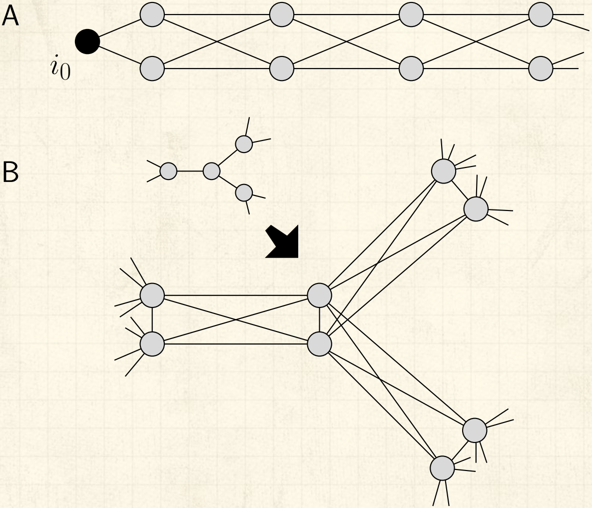

- Skewed influence distribution example.

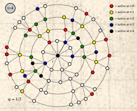


# Special subnetworks can act as triggers





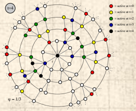


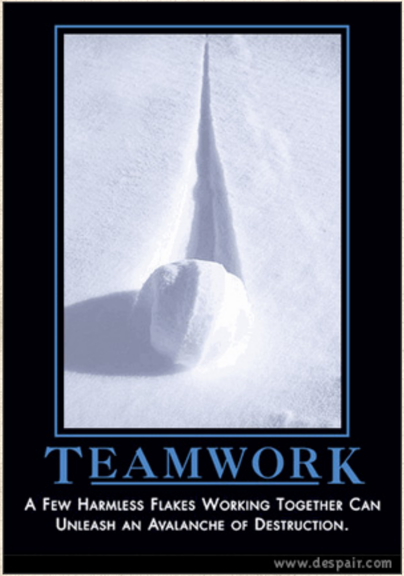
$\phi = 1/3$ for all nodes

# Outline





# The power of groups...

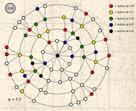



despair.com

"A few harmless flakes working together can unleash an avalanche of destruction."

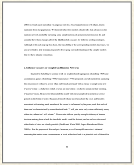






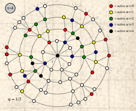
# Extensions





"Threshold Models of Social Influence"
Watts and Dodds,
The Oxford Handbook of Analytical Sociology, **34**, 475–497, 2009. [29]

Assumption of sparse interactions is good



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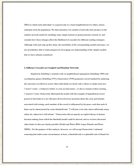

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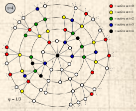
- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function



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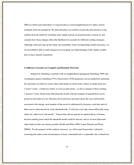

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- Assumption of sparse interactions is good
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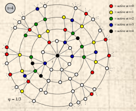
- Still, random networks don't represent all networks



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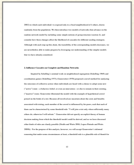

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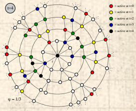
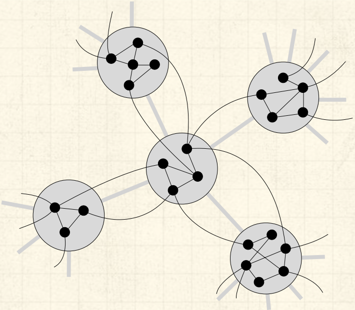
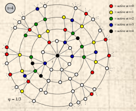
- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function
- Still, random networks don't represent all networks
- Major element missing: group structure



# Group structure—Ramified random networks



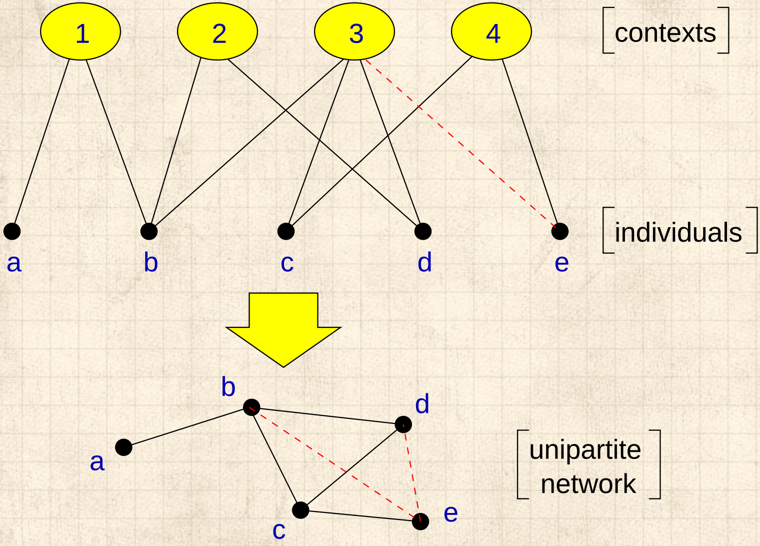
$p$ = intergroup connection probability
$q$ = intragroup connection probability.

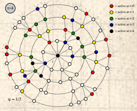


# Bipartite networks

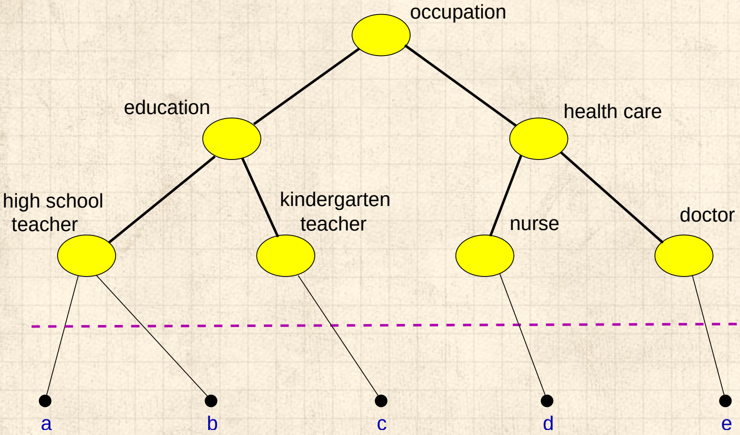


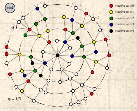




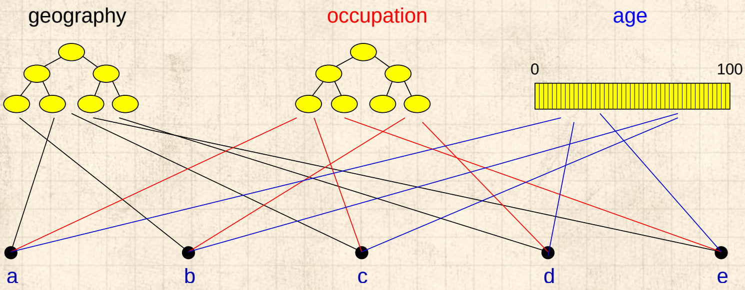



# Context distance

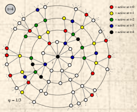


# Generalized affiliation model




(Blau & Schwartz, Simmel, Breiger)

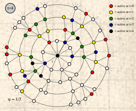


# Generalized affiliation model networks with triadic closure





- Connect nodes with probability $\propto e^{-\alpha d}$
  where
  $\alpha$ = homophily parameter
  and
  $d$ = distance between nodes (height of lowest common ancestor)



# Generalized affiliation model networks with triadic closure





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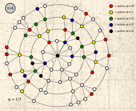

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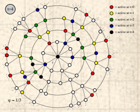
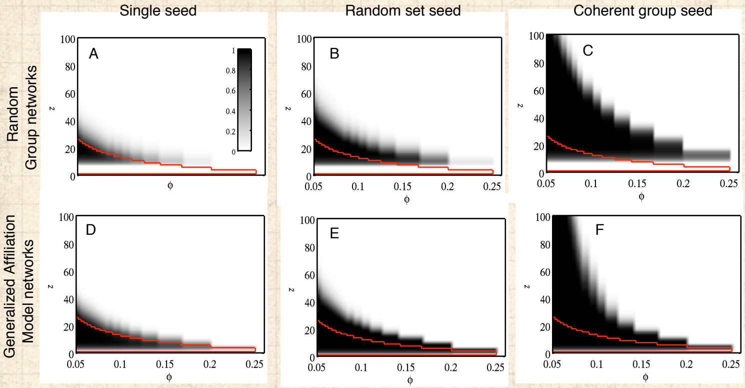
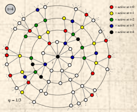


# Cascade windows for group-based networks





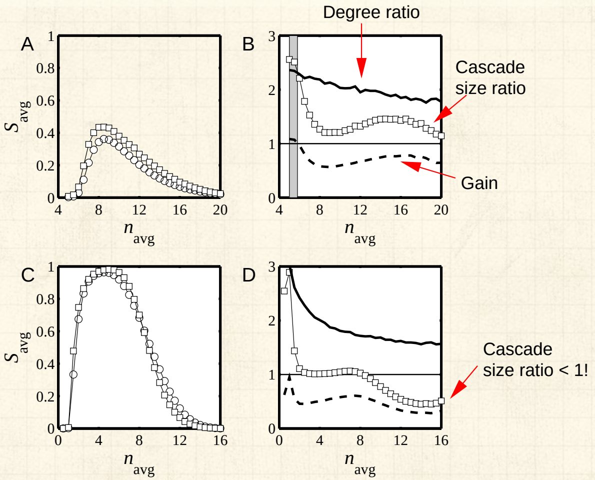


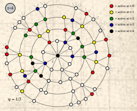



# Multiplier effect for group-based networks:







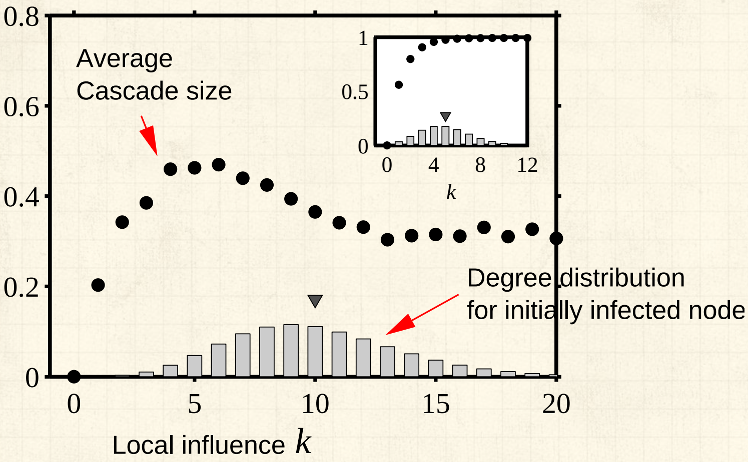



- Multiplier almost always below 1.

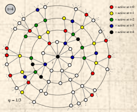
# Assortativity in group-based networks








- The most connected nodes aren't always the most 'influential.'



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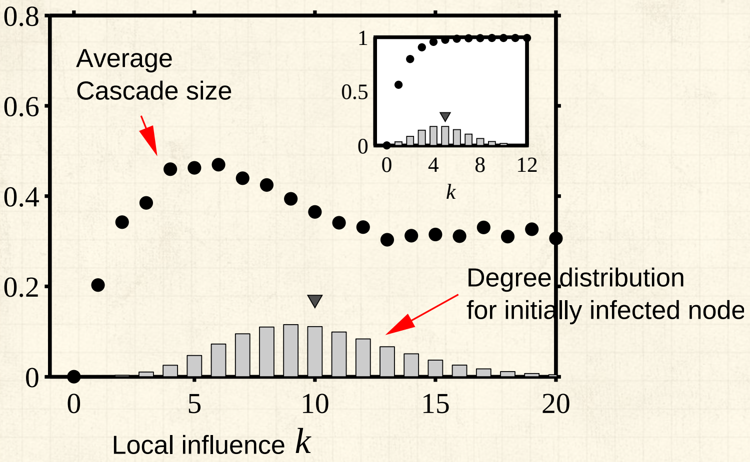
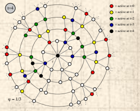


- The most connected nodes aren't always the most 'influential.'
- Degree assortativity is the reason.

# Social contagion

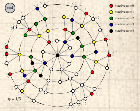
"Without followers, evil cannot spread." –Leonard Nimoy

## Summary

- 'Influential vulnerables' are key to spread.







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- ‘Influential vulnerables’ are key to spread.
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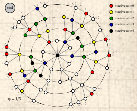

# Social contagion



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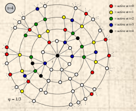
## Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.



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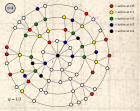

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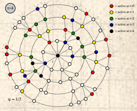

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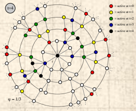

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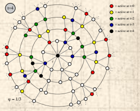

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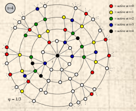
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.



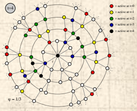
# Social contagion

## Implications

- Focus on the influential vulnerables.







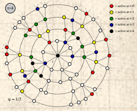
# Social contagion

## Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'







# Social contagion



## Implications

- Focus on the influential vulnerables.
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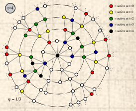
- Only simple ideas can spread by word-of-mouth.

  (Idea of opinion leaders spreads well...)



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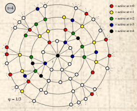
- Want enough individuals who will adopt and display.



# Social contagion





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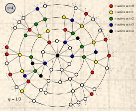
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).



# Social contagion



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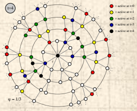
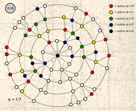
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.



# Spreading and unspreading: Empires

http://www.youtube.com/watch?v=FEaCfIp9qR4?rel=0



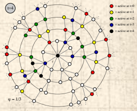
# References I



[1] A. Bentley, M. Earls, and M. J. O'Brien.
I'll Have What She's Having: Mapping Social Behavior.
MIT Press, Cambridge, MA, 2011.

[2] S. Bikhchandani, D. Hirshleifer, and I. Welch.
A theory of fads, fashion, custom, and cultural change as informational cascades.
J. Polit. Econ., 100:992–1026, 1992.

[3] S. Bikhchandani, D. Hirshleifer, and I. Welch.
Learning from the behavior of others: Conformity, fads, and informational cascades.
J. Econ. Perspect., 12(3):151–170, 1998. pdf



# References II

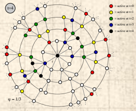




[4] J. M. Carlson and J. Doyle.
Highly optimized tolerance: A mechanism for power laws in designed systems.
Phys. Rev. E, 60(2):1412–1427, 1999. pdf

[5] J. M. Carlson and J. Doyle.
Highly optimized tolerance: Robustness and design in complex systems.
Phys. Rev. Lett., 84(11):2529–2532, 2000. pdf

[6] N. A. Christakis and J. H. Fowler.
The spread of obesity in a large social network over 32 years.
New England Journal of Medicine, 357:370–379, 2007. pdf



# References III

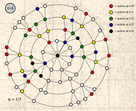




[7] N. A. Christakis and J. H. Fowler.
The collective dynamics of smoking in a large social network.
New England Journal of Medicine, 358:2249–2258, 2008. pdf

[8] R. B. Cialdini.
Influence: Science and Practice.
Allyn and Bacon, Boston, MA, 4th edition, 2000.

[9] P. S. Dodds, K. D. Harris, and C. M. Danforth.
Limited Imitation Contagion on random networks: Chaos, universality, and unpredictability.
Phys. Rev. Lett., 110:158701, 2013. pdf



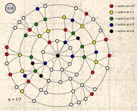
# References IV



[10] P. S. Dodds, K. D. Harris, and J. L. Payne.
Direct, phyiscally motivated derivation of the contagion condition for spreading processes on generalized random networks.
Phys. Rev. E, 83:056122, 2011. pdf

[11] J. H. Fowler and N. A. Christakis.
Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study.
BMJ, 337:article #2338, 2008. pdf

[12] M. Gladwell.
The Tipping Point.
Little, Brown and Company, New York, 2000.

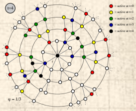


# References V

[13] J. P. Gleeson.
Cascades on correlated and modular random networks.
Phys. Rev. E, 77:046117, 2008. pdf

[14] J. P. Gleeson and D. J. Cahalane.
Seed size strongly affects cascades on random networks.
Phys. Rev. E, 75:056103, 2007. pdf

[15] M. Granovetter.
Threshold models of collective behavior.
Am. J. Sociol., 83(6):1420–1443, 1978. pdf



# References VI

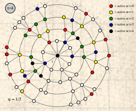




[16] M. Granovetter and R. Soong.
Threshold models of diversity: Chinese restaurants, residential segregation, and the spiral of silence.
Sociological Methodology, 18:69–104, 1988. pdf

[17] M. S. Granovetter and R. Soong.
Threshold models of interpersonal effects in consumer demand.
J. Econ. Behav. Organ., 7:83–99, 1986. pdf

[18] K. D. Harris, C. M. Danforth, and P. S. Dodds.
Dynamical influence processes on networks: General theory and applications to social contagion.
Phys. Rev. E, 88:022816, 2013. pdf



# References VII

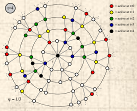

[19] E. Katz and P. F. Lazarsfeld.
Personal Influence.
The Free Press, New York, 1955.

[20] T. Kuran.
Now out of never: The element of surprise in the east european revolution of 1989.
World Politics, 44:7–48, 1991. pdf

[21] T. Kuran.
Private Truths, Public Lies: The Social Consequences of Preference Falsification.
Harvard University Press, Cambridge, MA, Reprint edition, 1997.

[22] T. Pratchett.
The Truth.
HarperCollins, 2000.



# References VIII

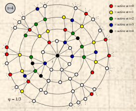


[23] T. C. Schelling.
Dynamic models of segregation.
J. Math. Sociol., 1:143–186, 1971. pdf

[24] T. C. Schelling.
Hockey helmets, concealed weapons, and daylight saving: A study of binary choices with externalities.
J. Conflict Resolut., 17:381–428, 1973. pdf

[25] T. C. Schelling.
Micromotives and Macrobehavior.
Norton, New York, 1978.

[26] D. Sornette.
Critical Phenomena in Natural Sciences.
Springer-Verlag, Berlin, 1st edition, 2003.



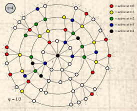
# References IX



[27] D. J. Watts.
A simple model of global cascades on random networks.
Proc. Natl. Acad. Sci., 99(9):5766–5771, 2002.
pdf

[28] D. J. Watts and P. S. Dodds.
Influentials, networks, and public opinion formation.
Journal of Consumer Research, 34:441–458, 2007.
pdf

[29] D. J. Watts and P. S. Dodds.
Threshold models of social influence.
In P. Hedström and P. Bearman, editors, The Oxford Handbook of Analytical Sociology, chapter 20, pages 475–497. Oxford University Press, Oxford, UK, 2009. pdf



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