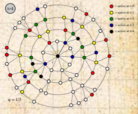
Social Contagion

Principles of Complex Systems | @pocsvox
CSYS/MATH 300, Fall, 2017

Prof. Peter Dodds | @peterdodds

Dept. of Mathematics & Statistics | Vermont Complex Systems Center
Vermont Advanced Computing Core | University of Vermont



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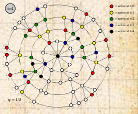

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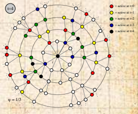
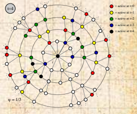
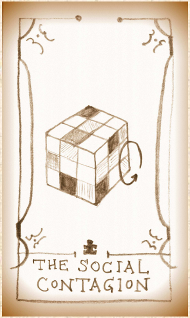


Outline




THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
THE WELL OF SCALES
THE LAWS OF DECAYING POWER
MINISTRY OF RANDOM WALKS
THE UNEXPECTED TRANSFIGURATION
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 SUPPLY MOST FAIR
THE SUPPLY TO THE MOST
THE MANY TALES OF MANY TAILS
THE MEASURING
THE DATA POOR
THE POURING DATA
THE CHARMS OF THE MANY WRONG PATHS
THE KNOWLEDGE OF DEAD MONKS
THE DOORS THAT SHOULD NOT BE OPENED
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
It was the best of times,
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE ARK OF THE RANDOM NETWORK
THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
THE STRANGENESS OF FRIENDS
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
CLASSIFIED
PHOENIX
BIO HAZARD
THE CONTAGION
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE RATIO OF GAIN
THE THRESHOLDS OF THE MIND
THE SOCIAL WILD
THE MECHANICS OF FAME
THE STORIES CONTAGIOUS
THE PATHS OF UNIVERSALITY
THE DEPENDENT PATHS
THE TROUSERS OF BIFURCATING REALITIES
THE UNKNOWN MECHANISM
THE JOHN DORY
THE STORYTELLERS
THE ADJACENT NARRATIVES
THE END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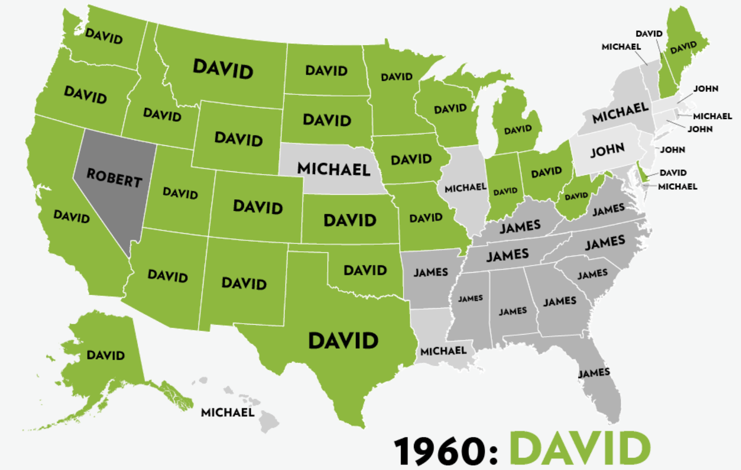

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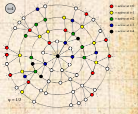

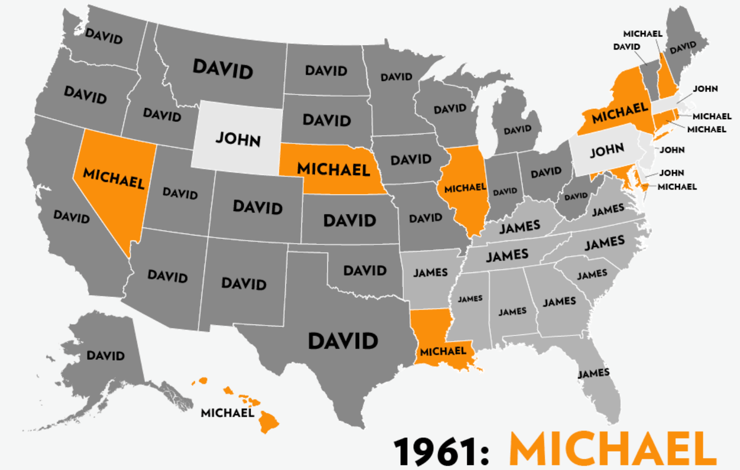

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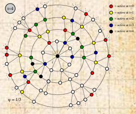

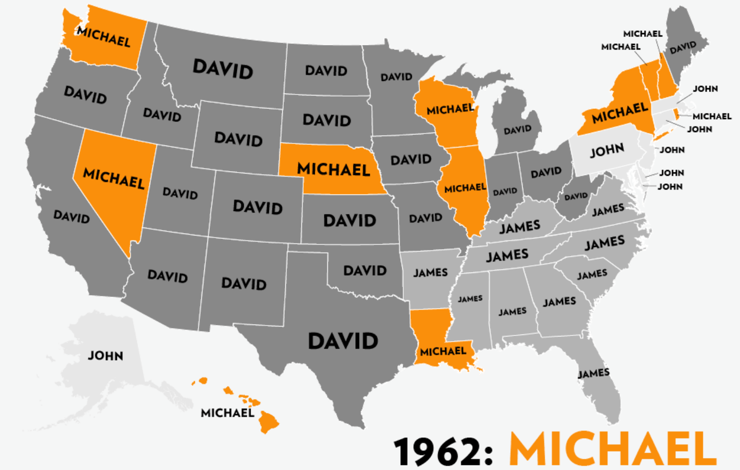

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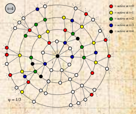

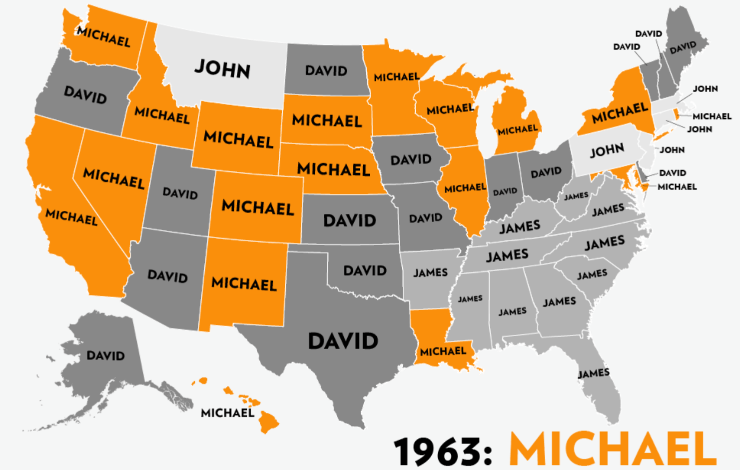

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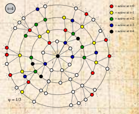

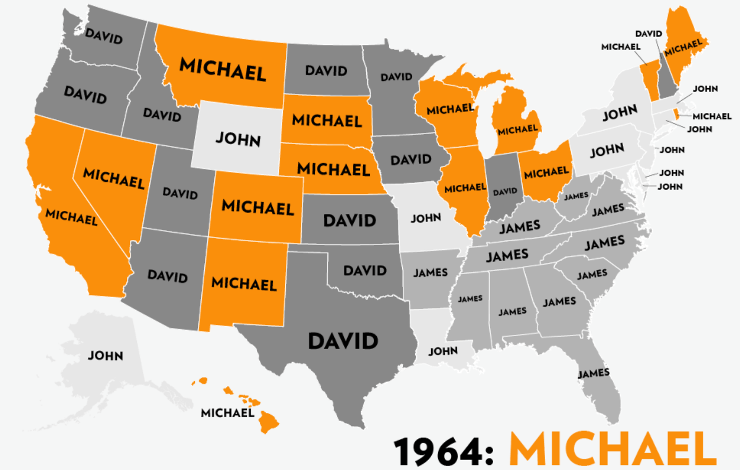

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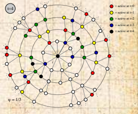

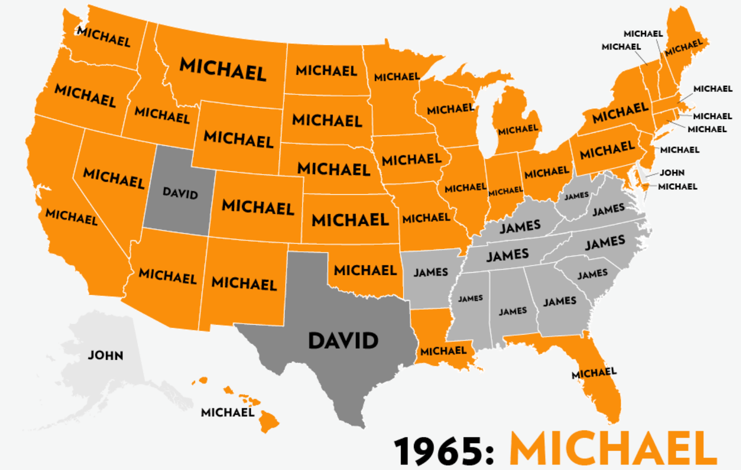

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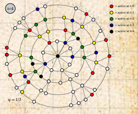

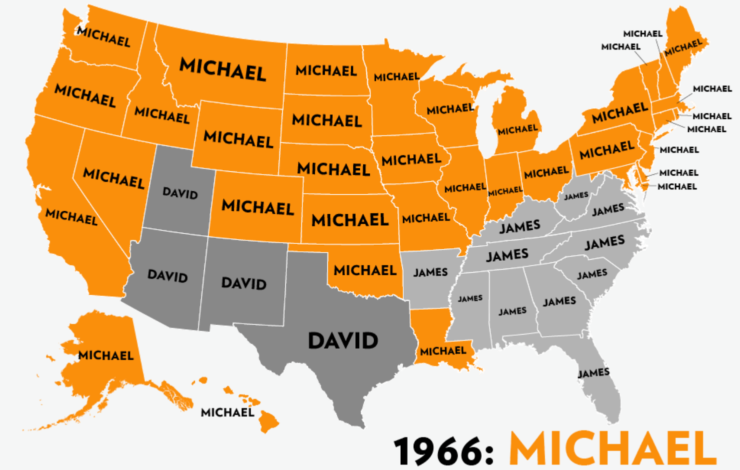

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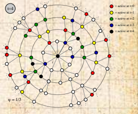

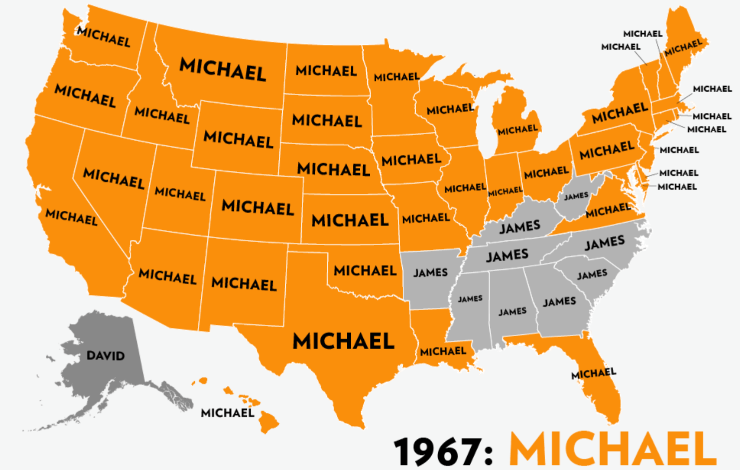

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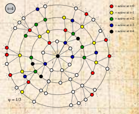

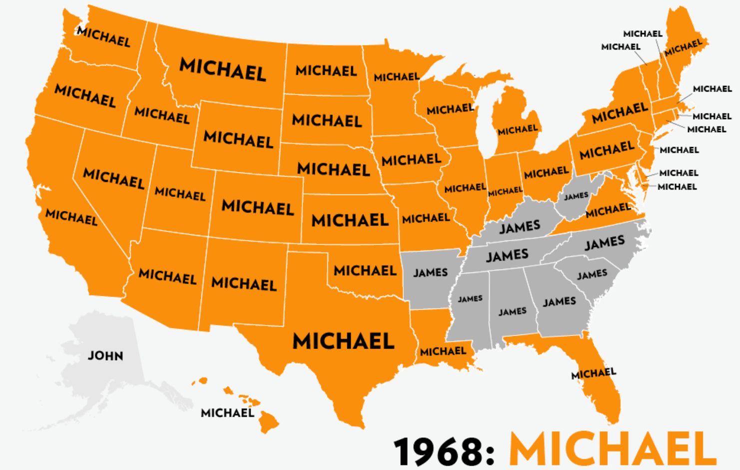

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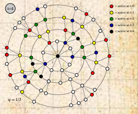

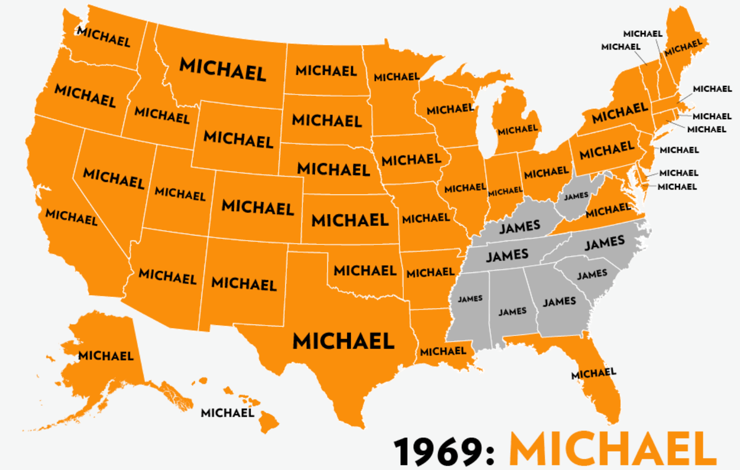

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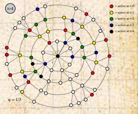

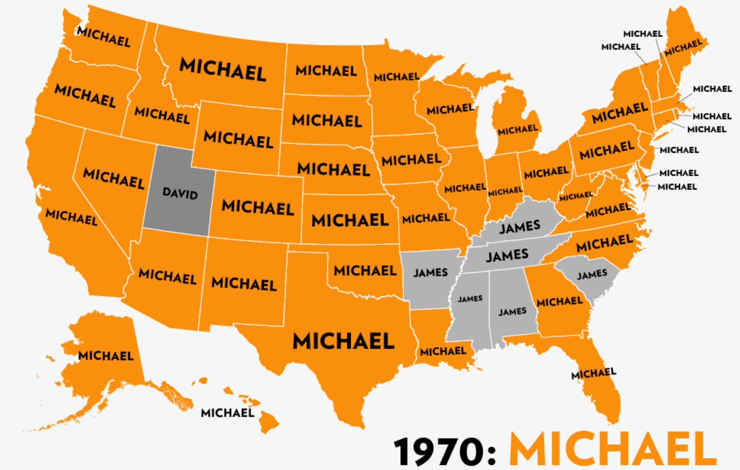

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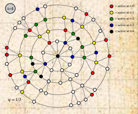

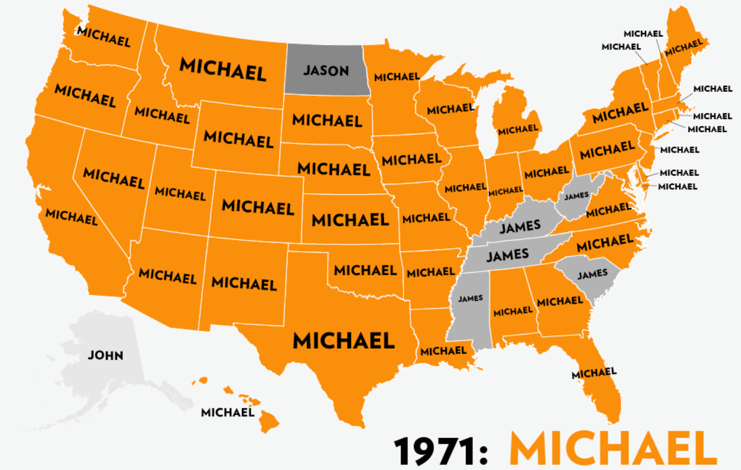

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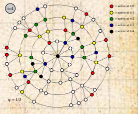

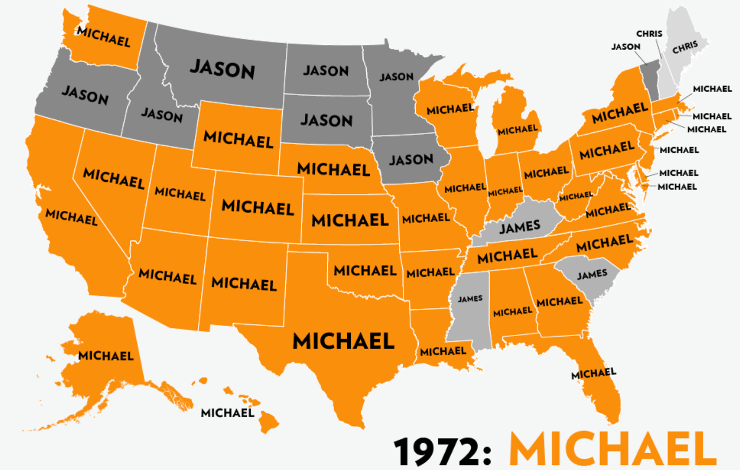

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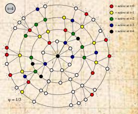

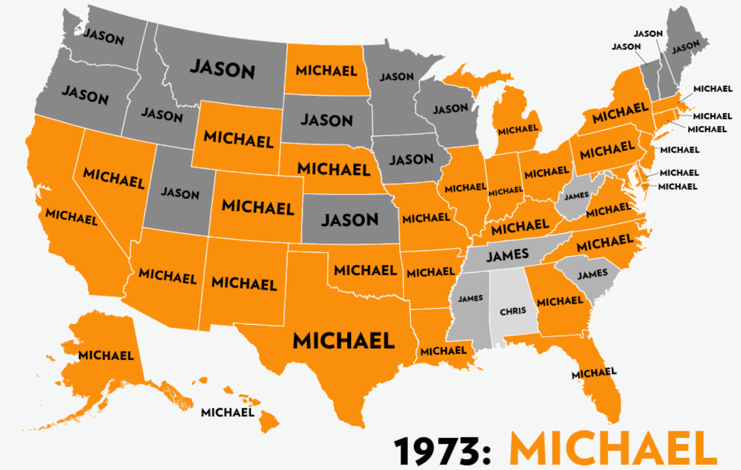

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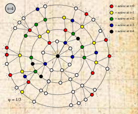

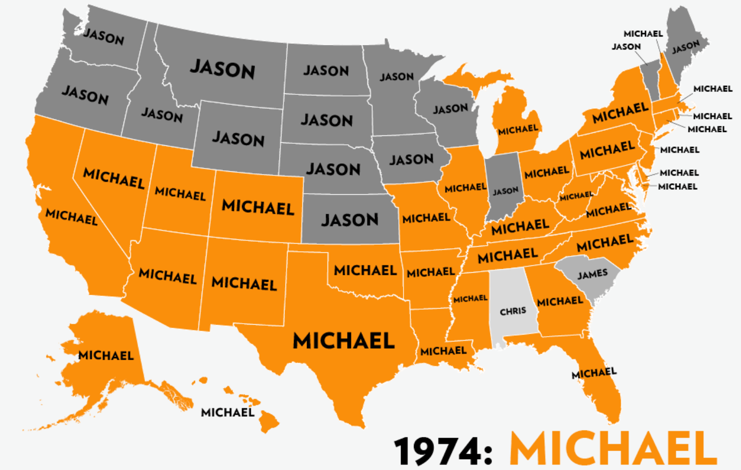

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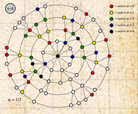

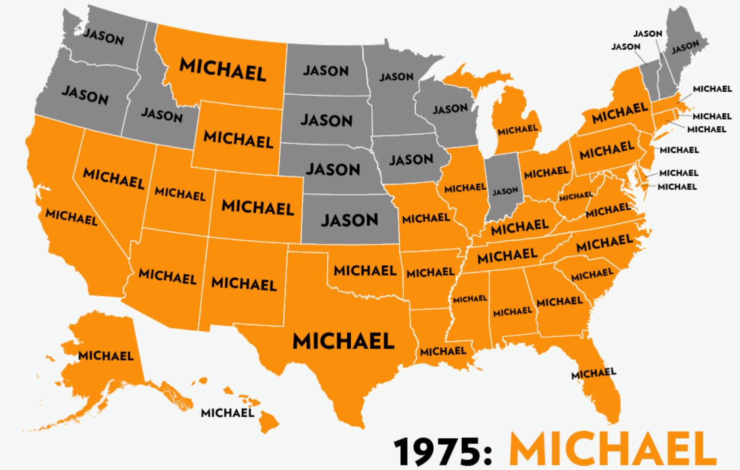

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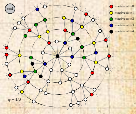

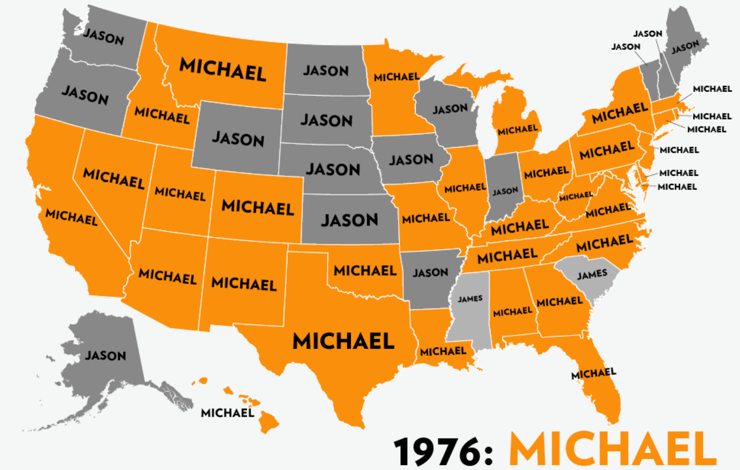

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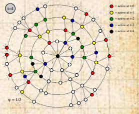

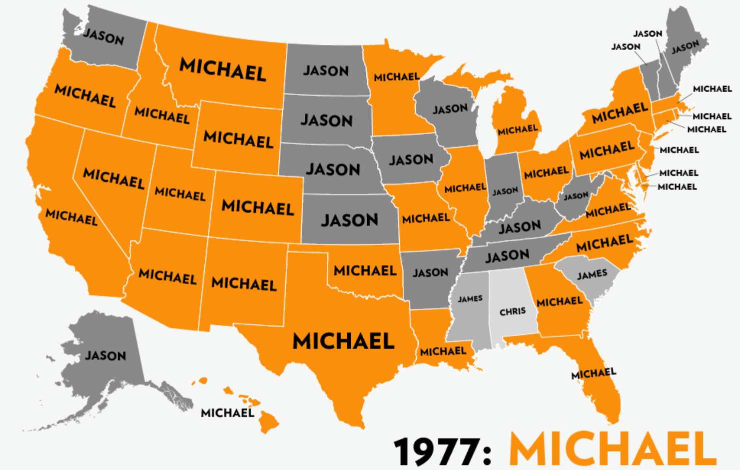

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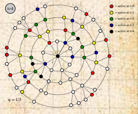

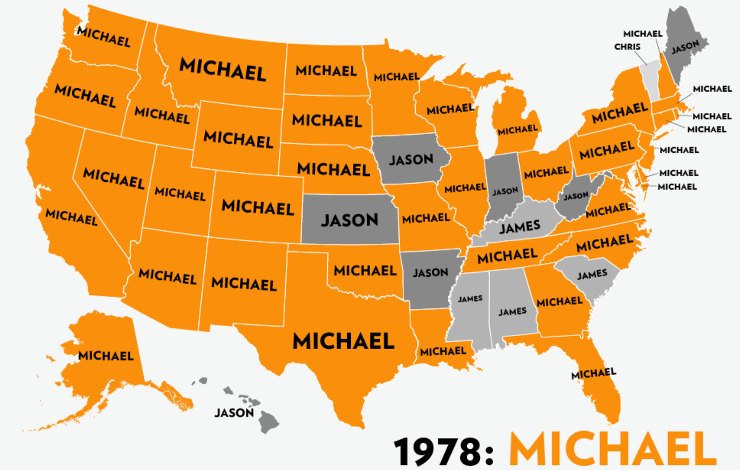

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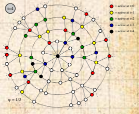

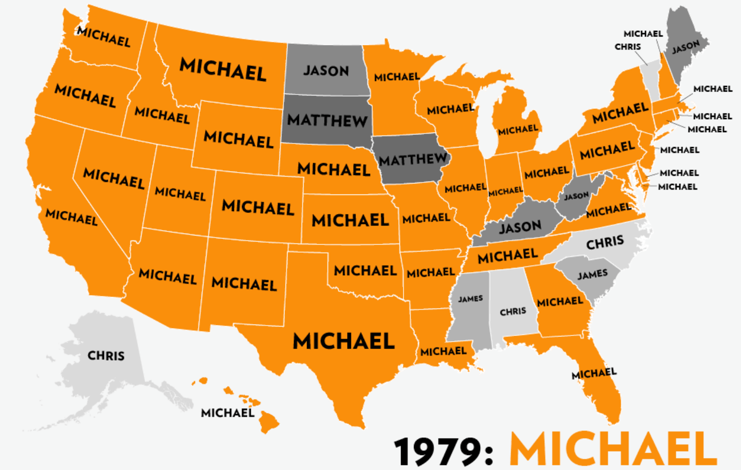

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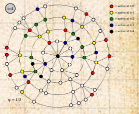

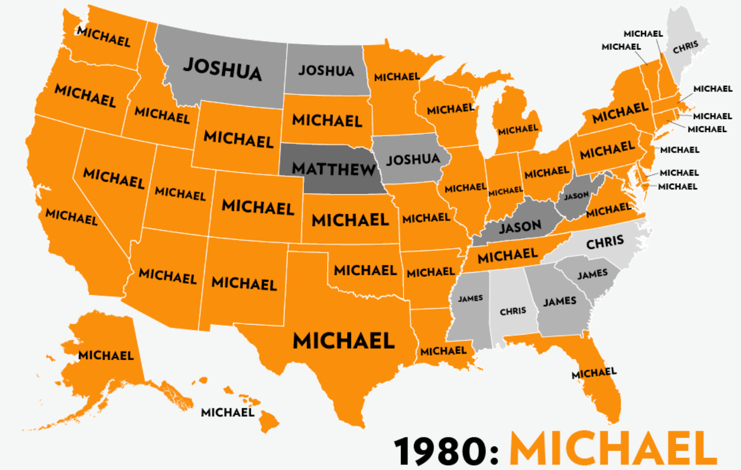

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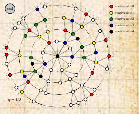

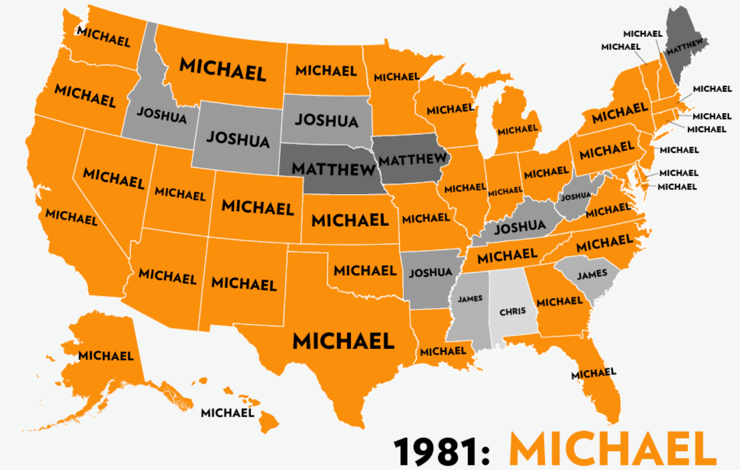

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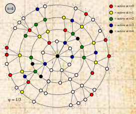

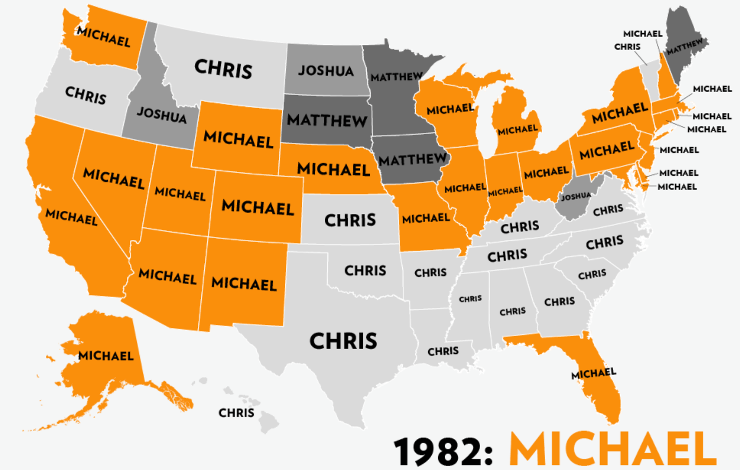

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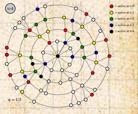

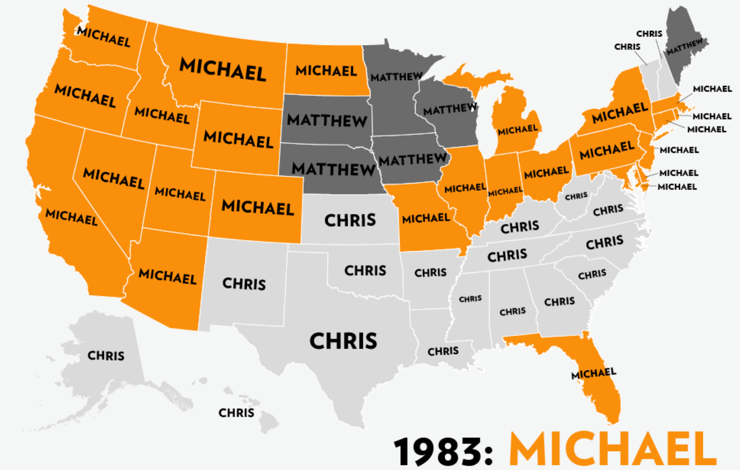

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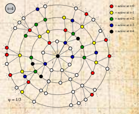

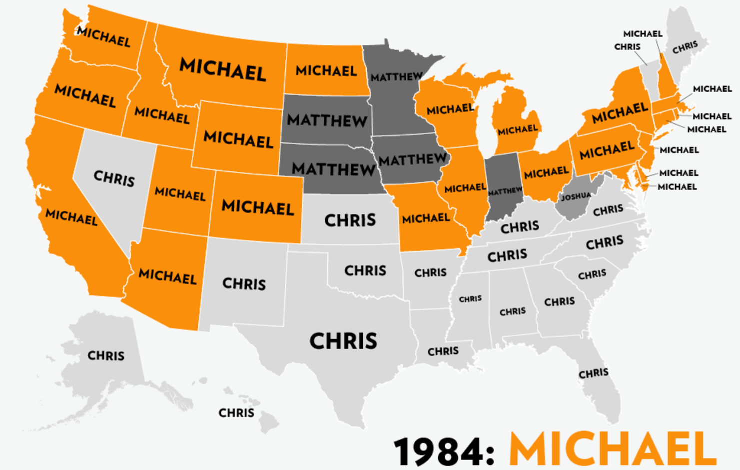

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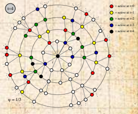

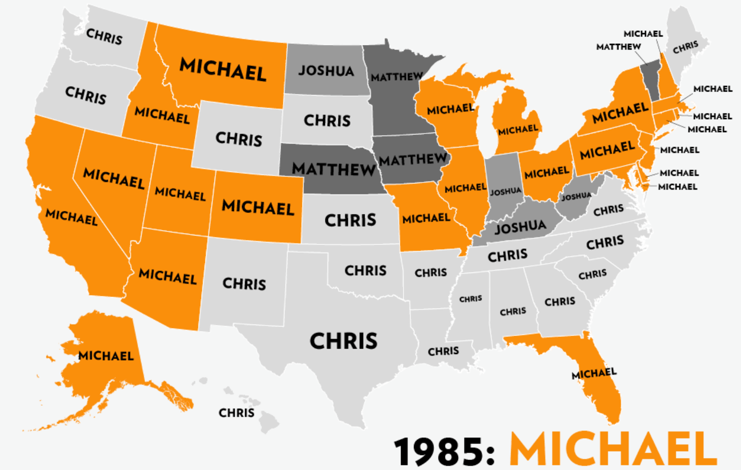

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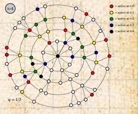

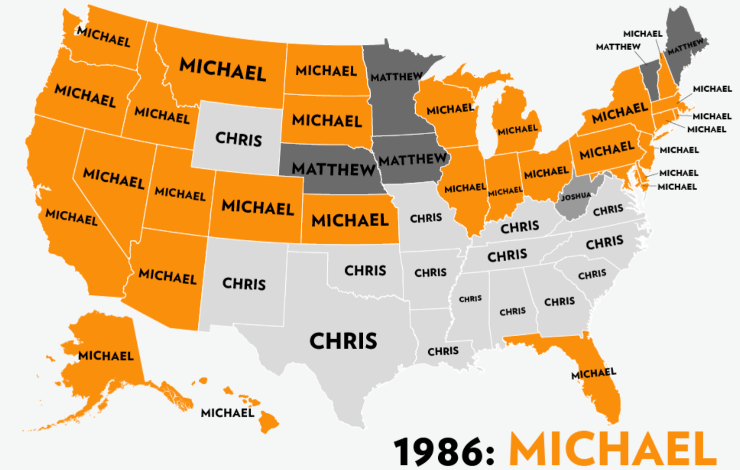

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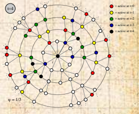

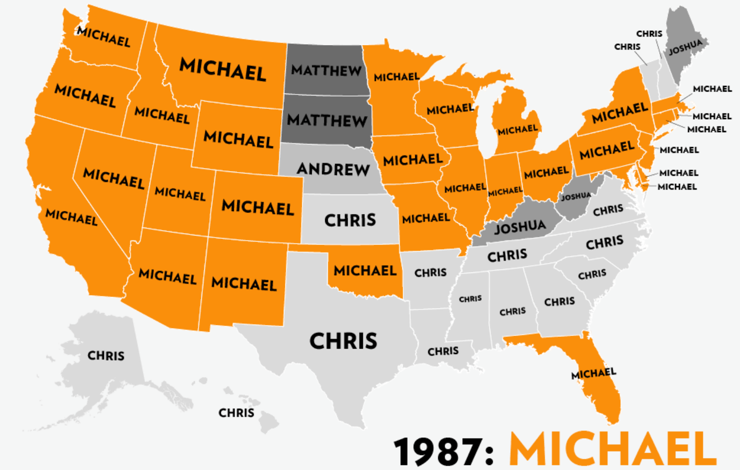

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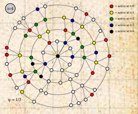

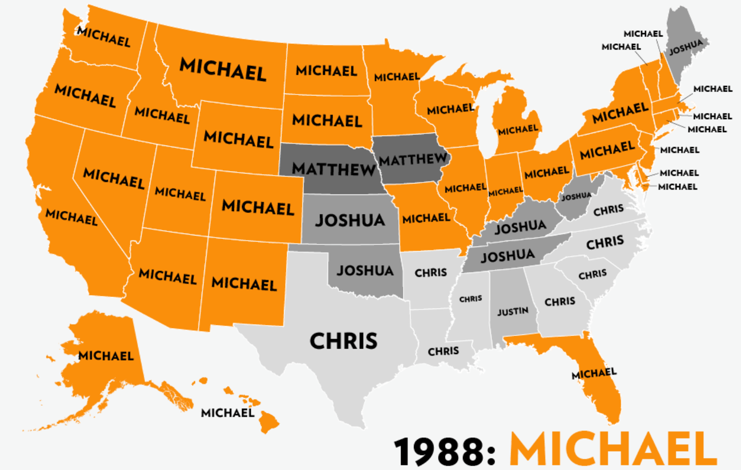

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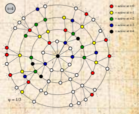

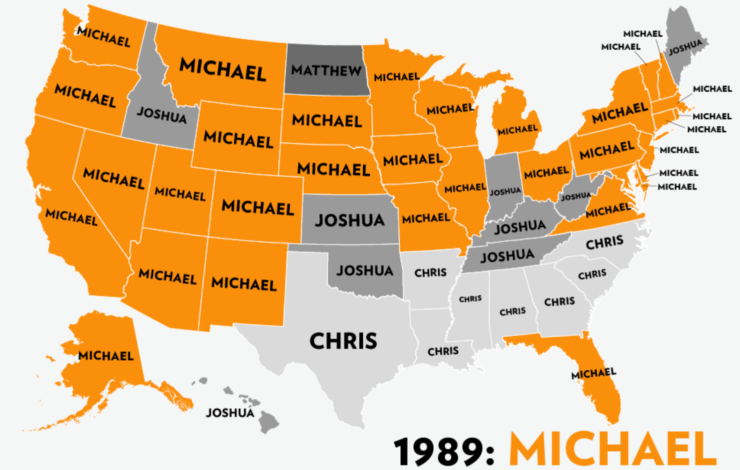

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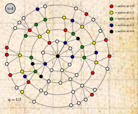

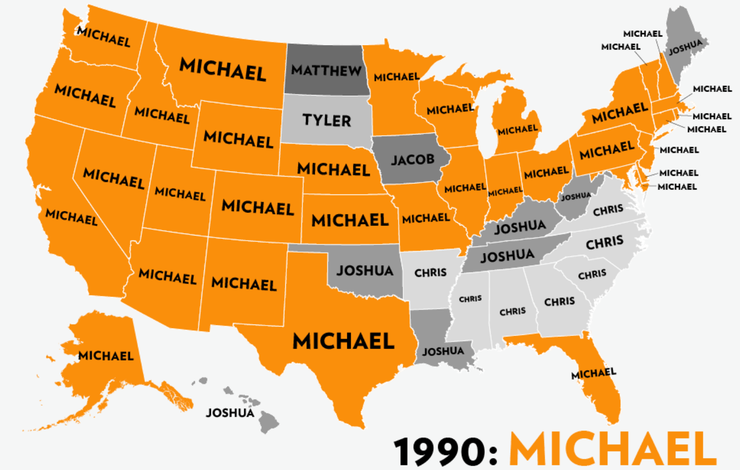

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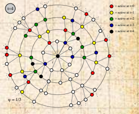

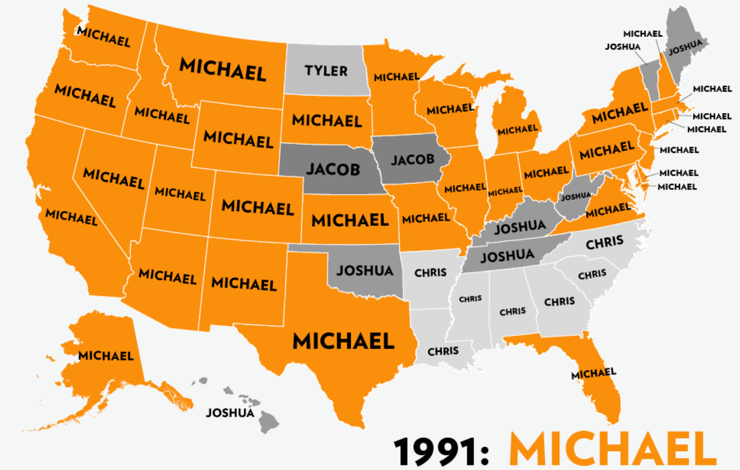

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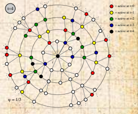

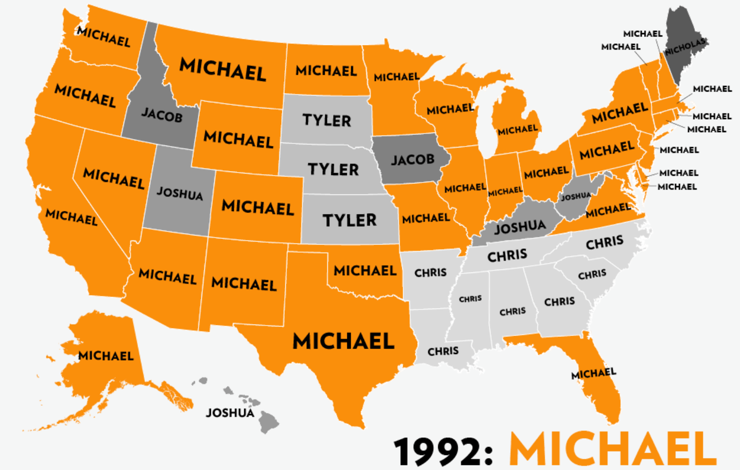

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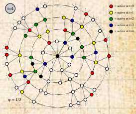

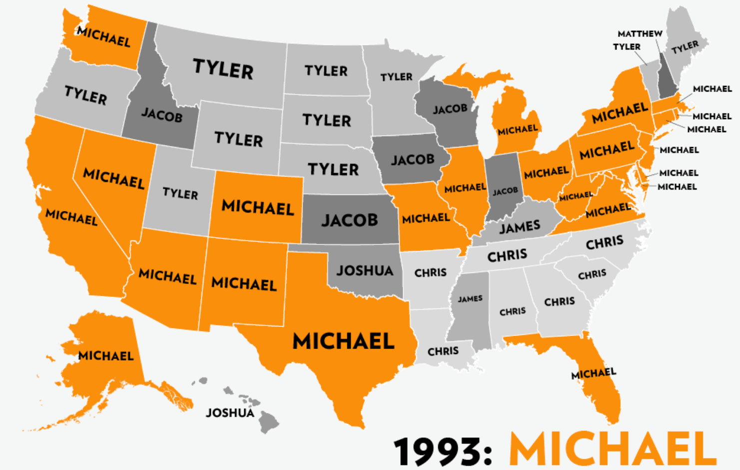

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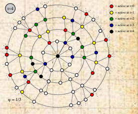

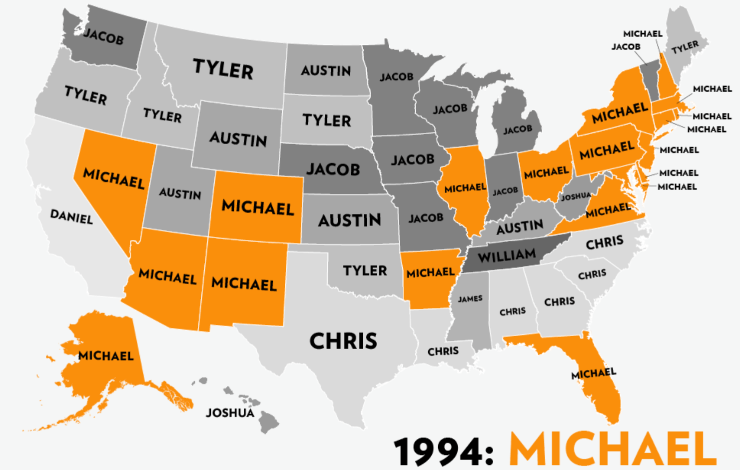

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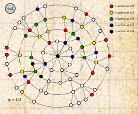

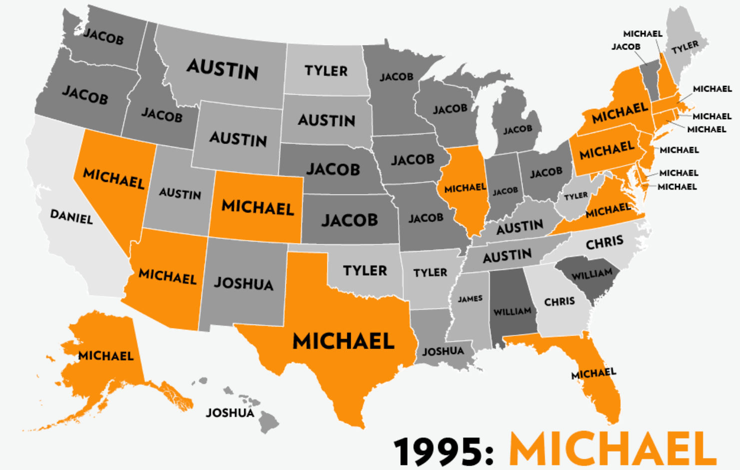

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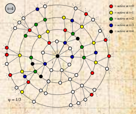

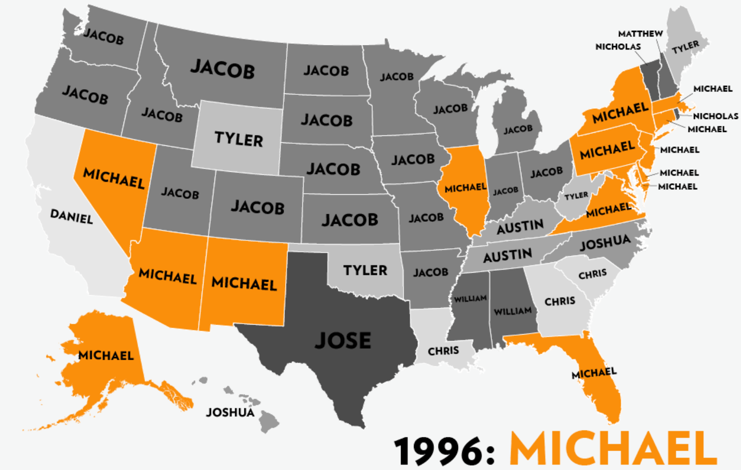

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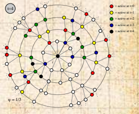

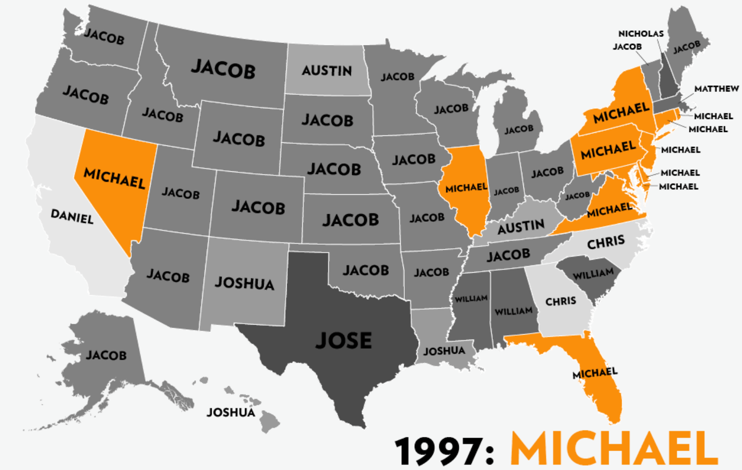

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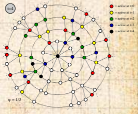

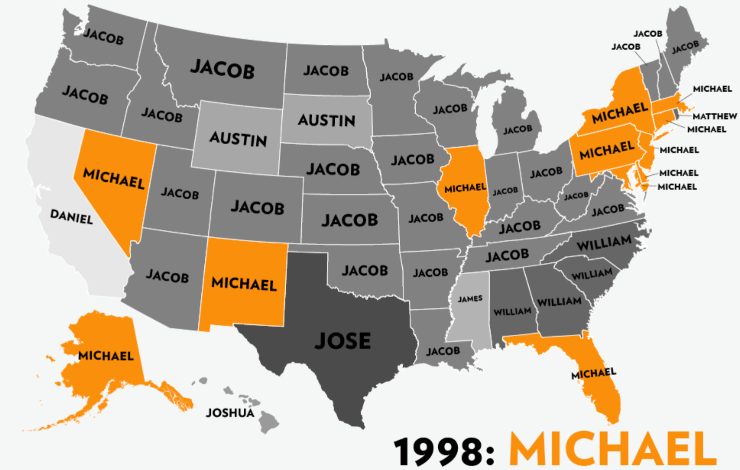

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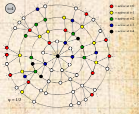

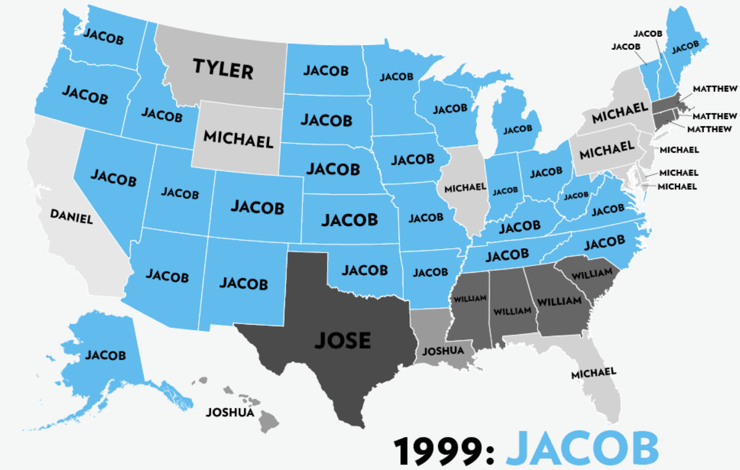

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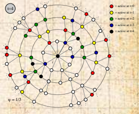

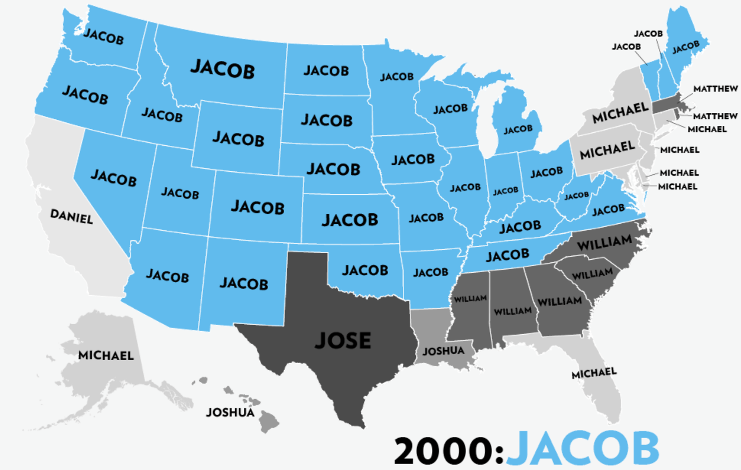

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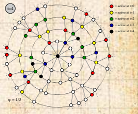

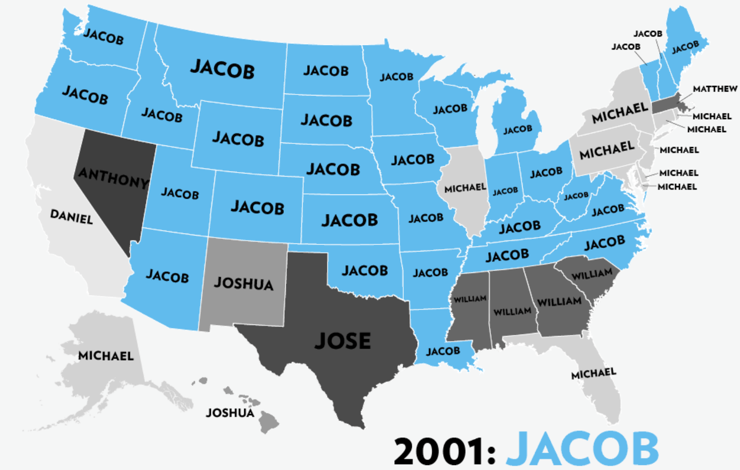

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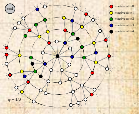

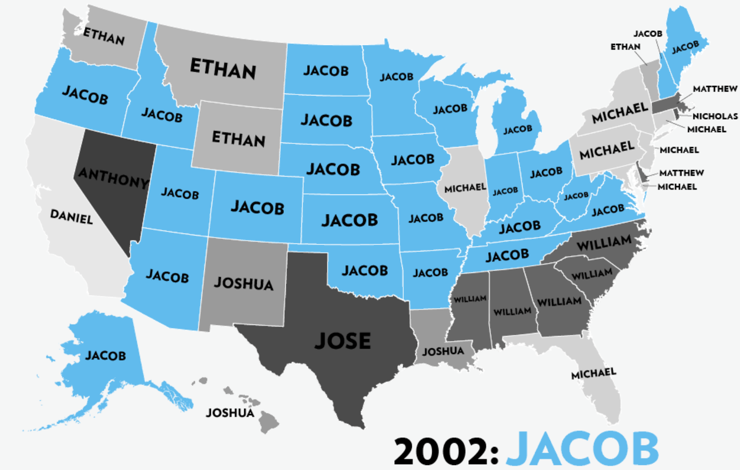

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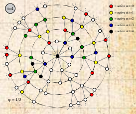

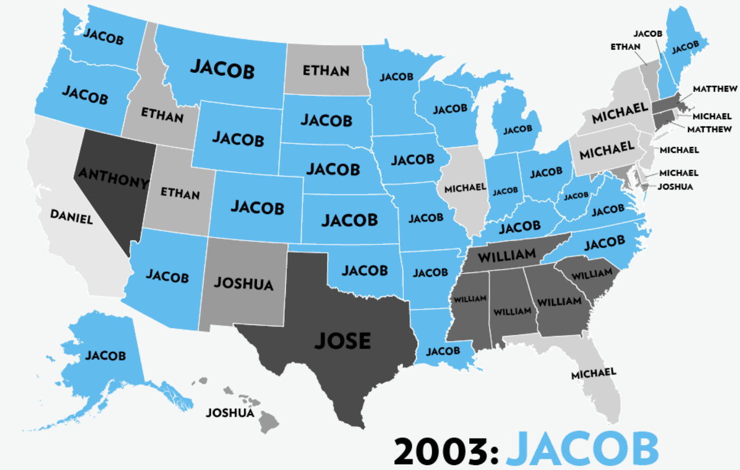

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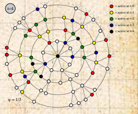

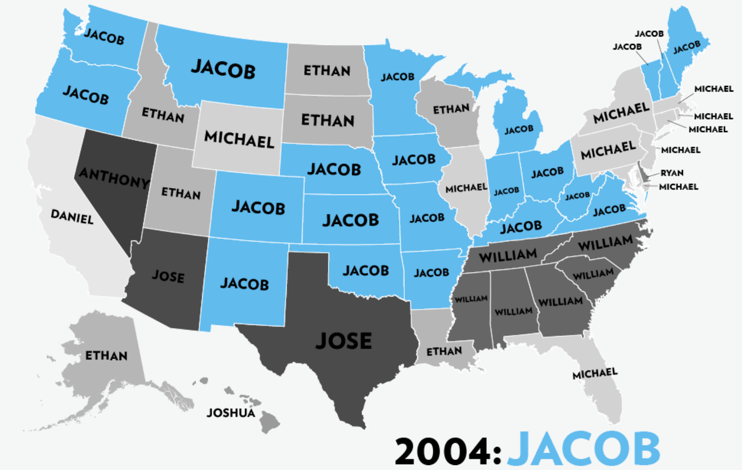

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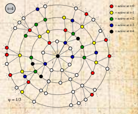

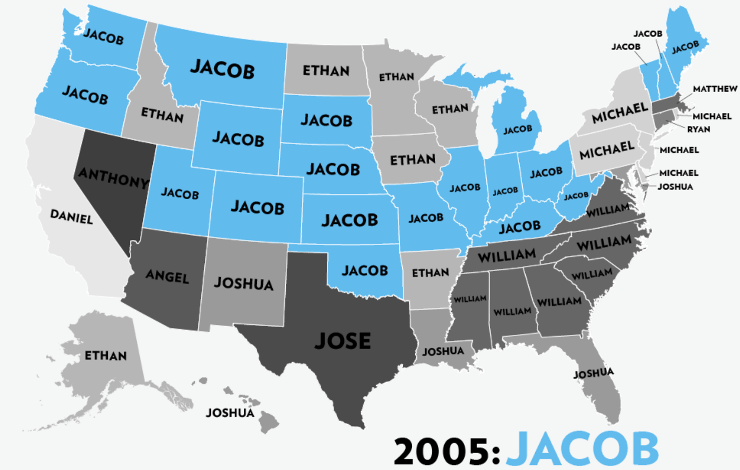

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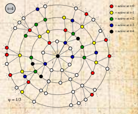

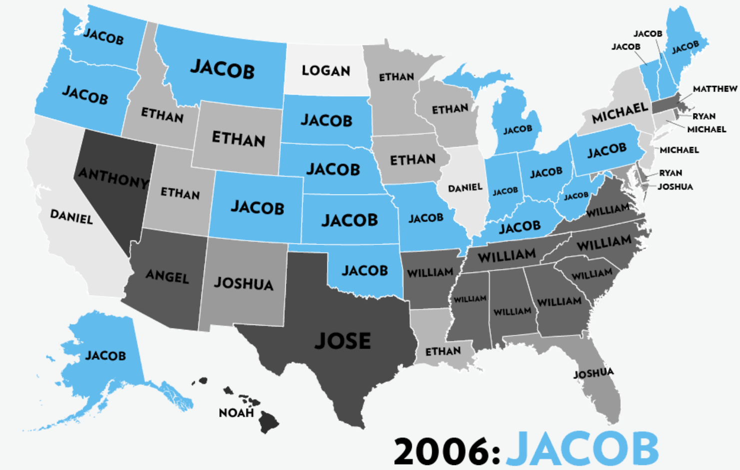

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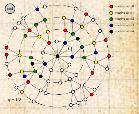

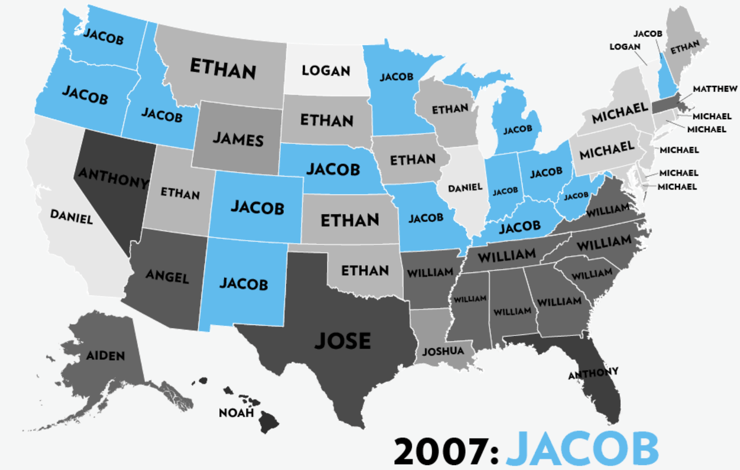

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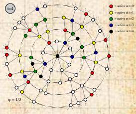

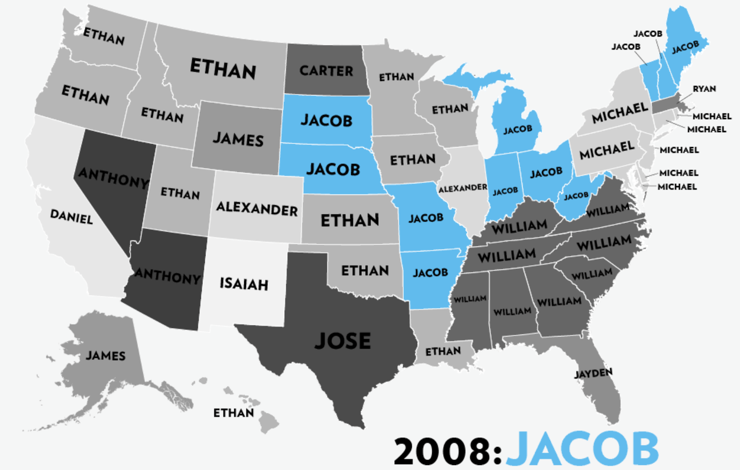

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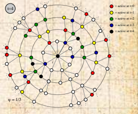

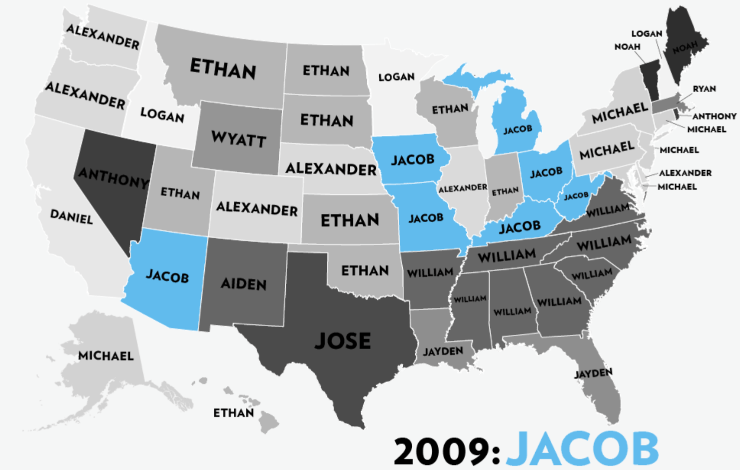

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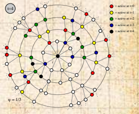

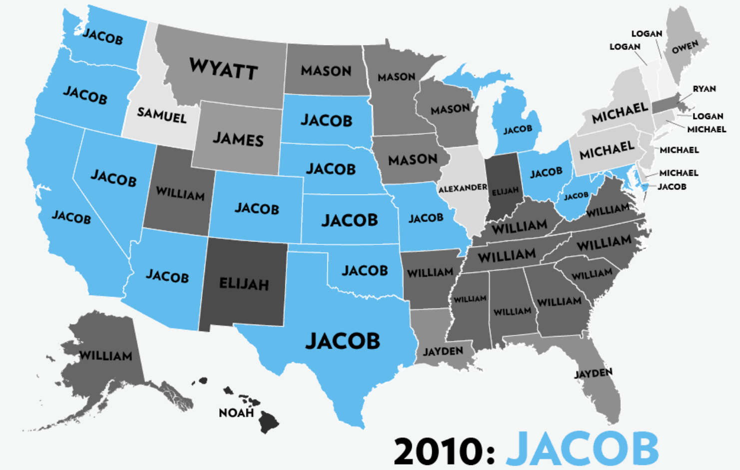

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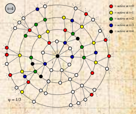

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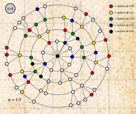

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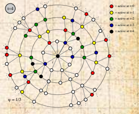

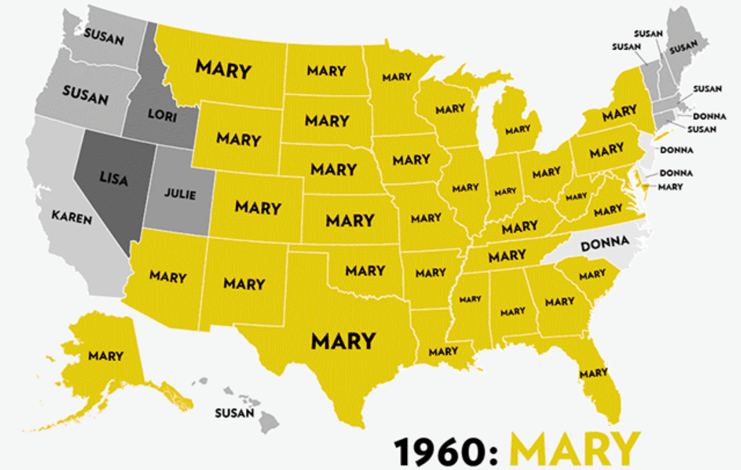

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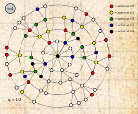

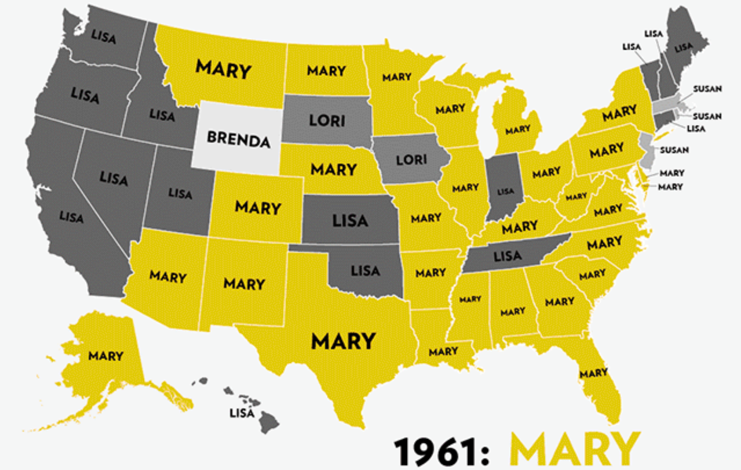

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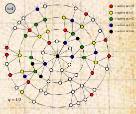

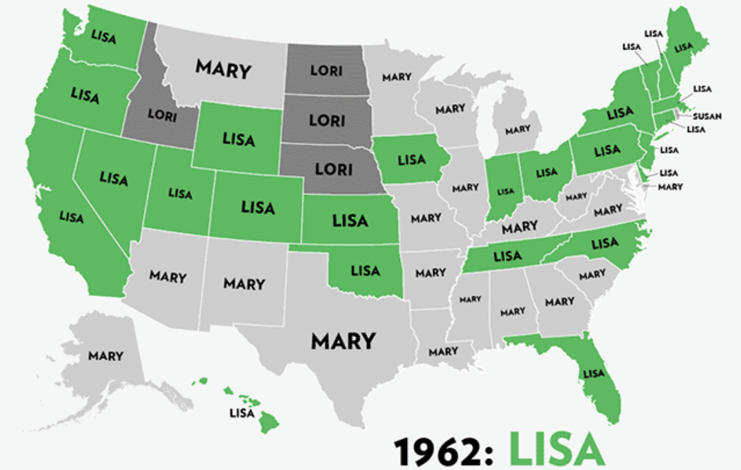

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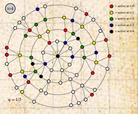

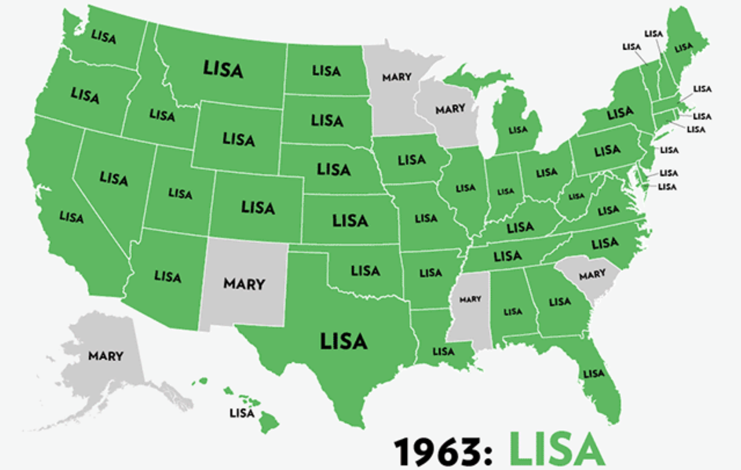

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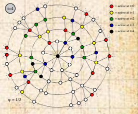

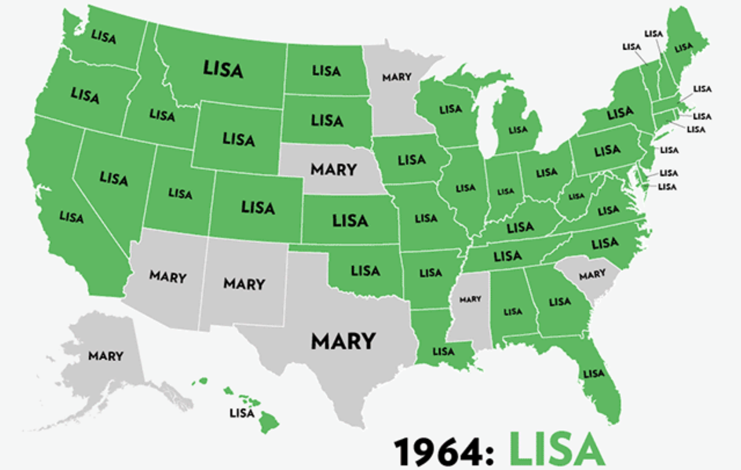

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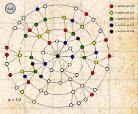

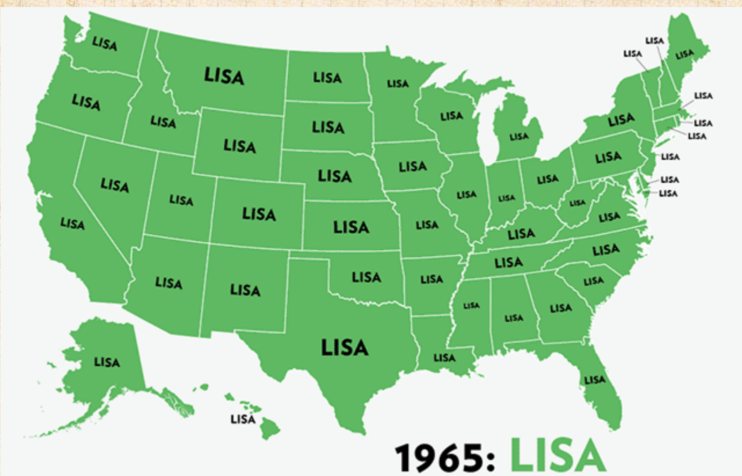

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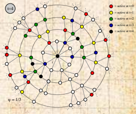

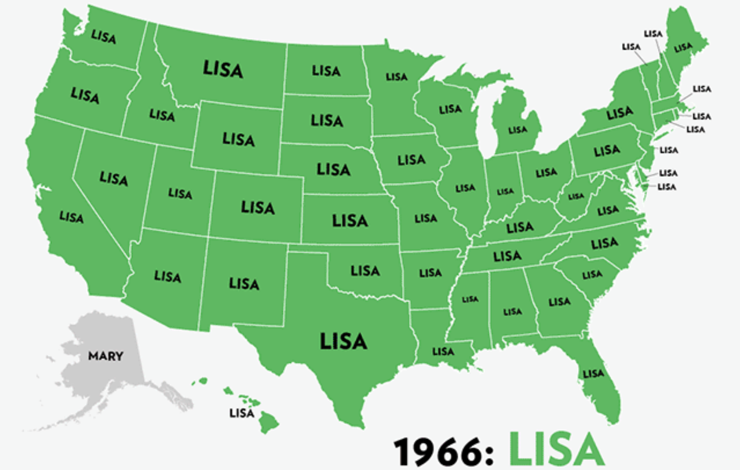

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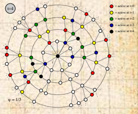

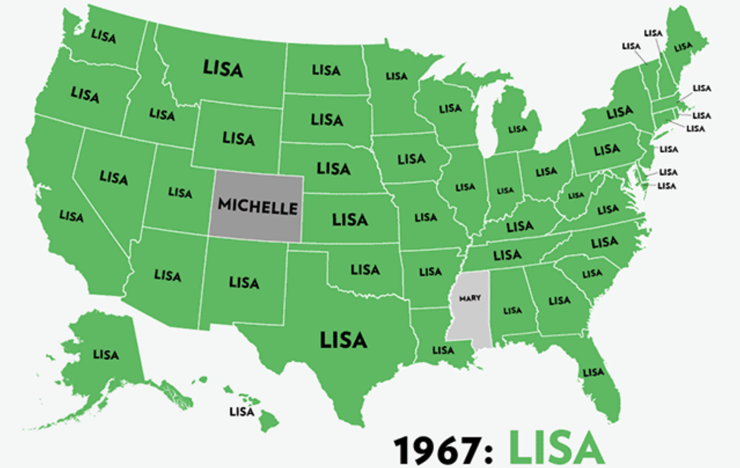

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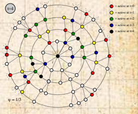

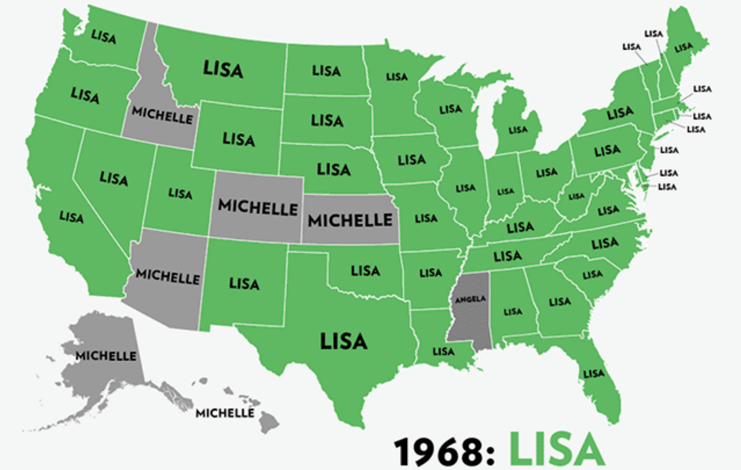

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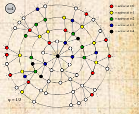

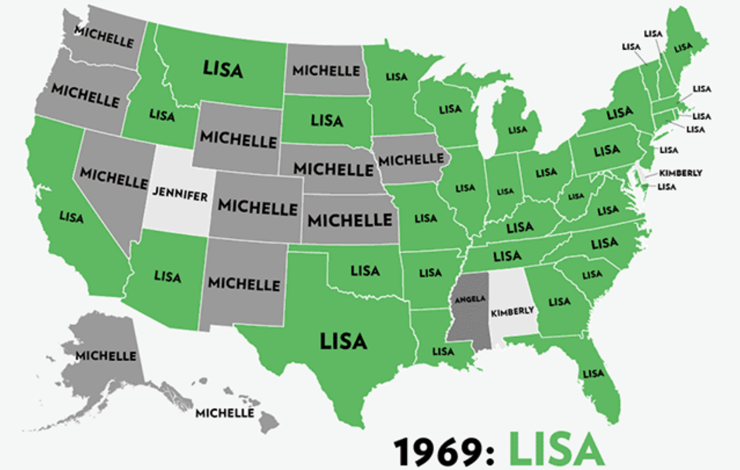

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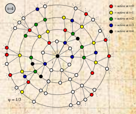

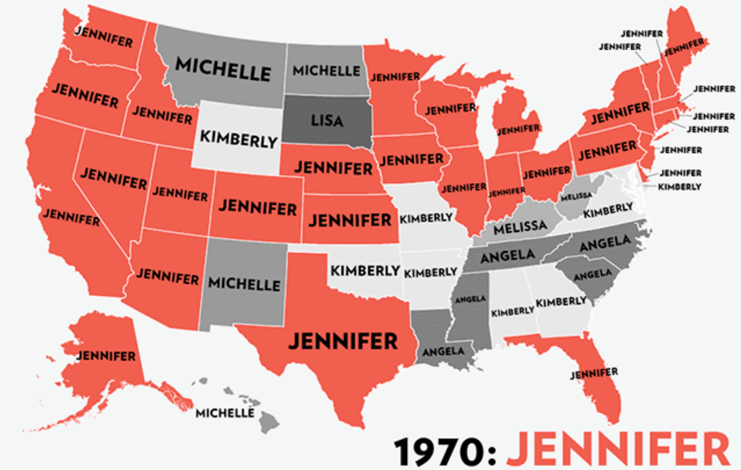

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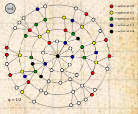

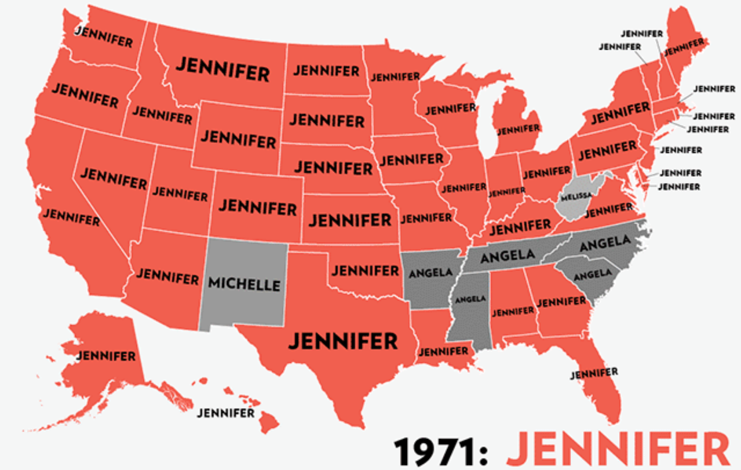

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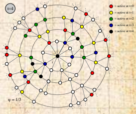

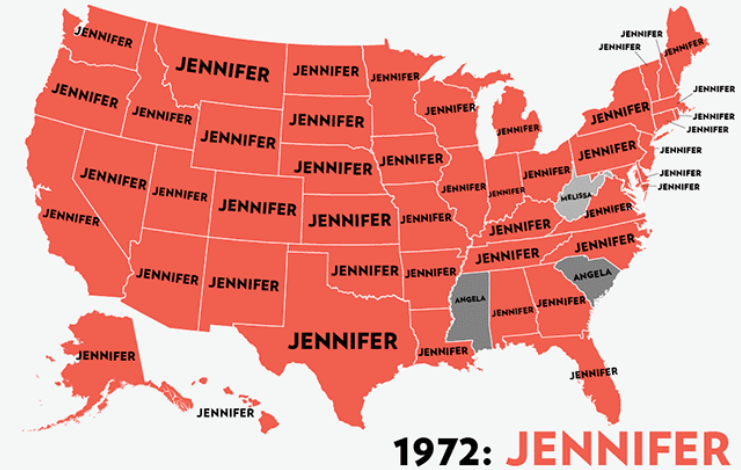

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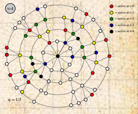

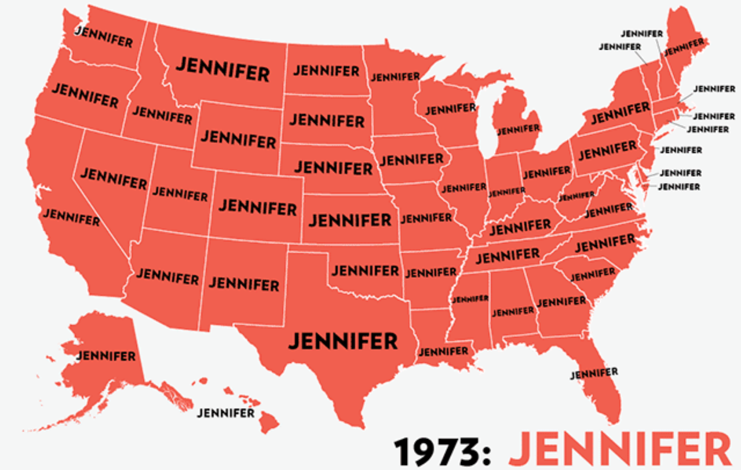

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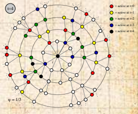

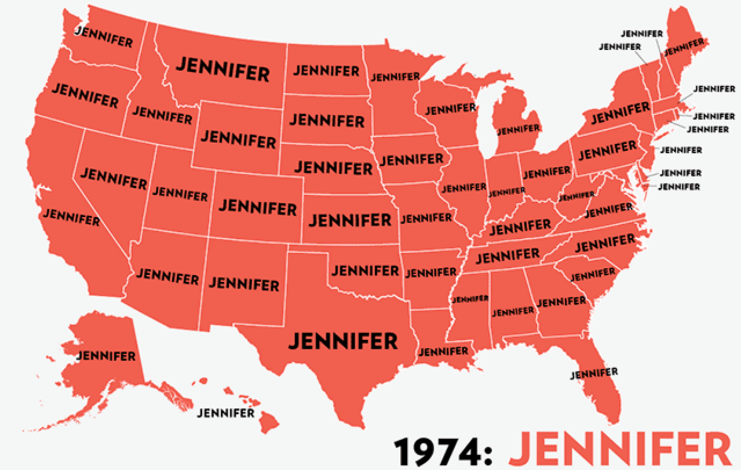

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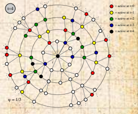

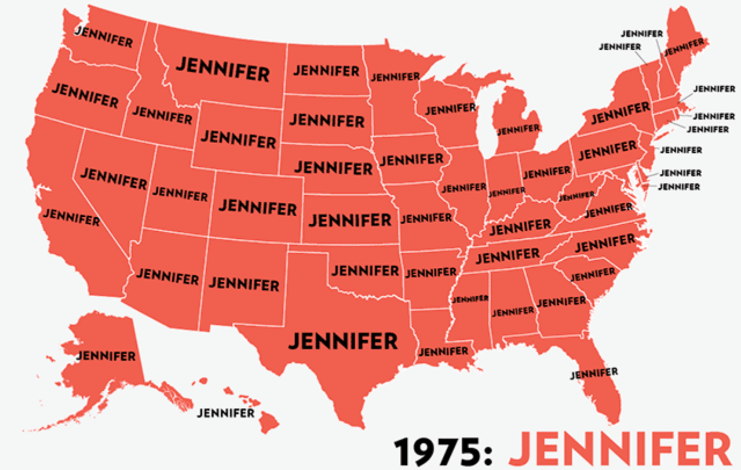

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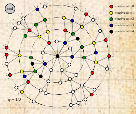

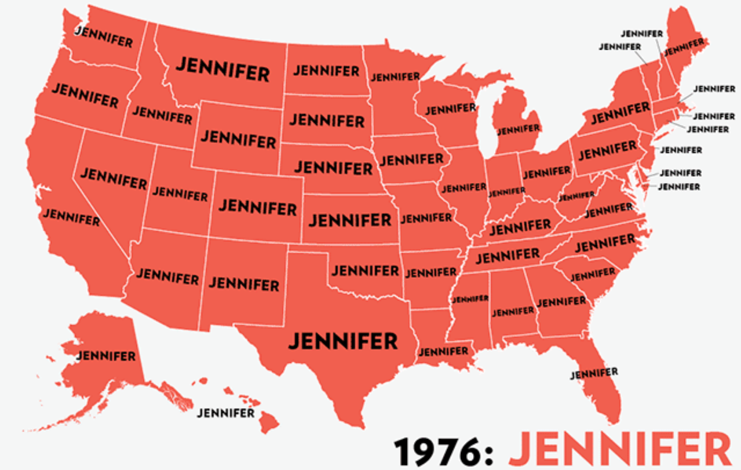

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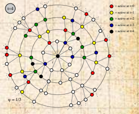

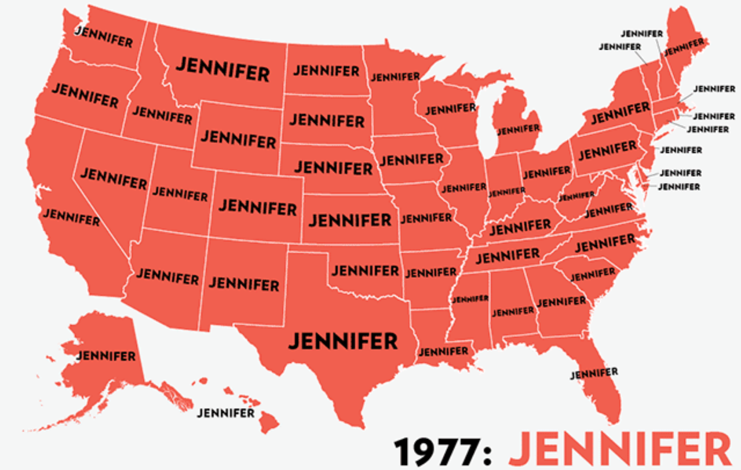

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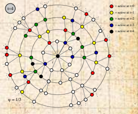

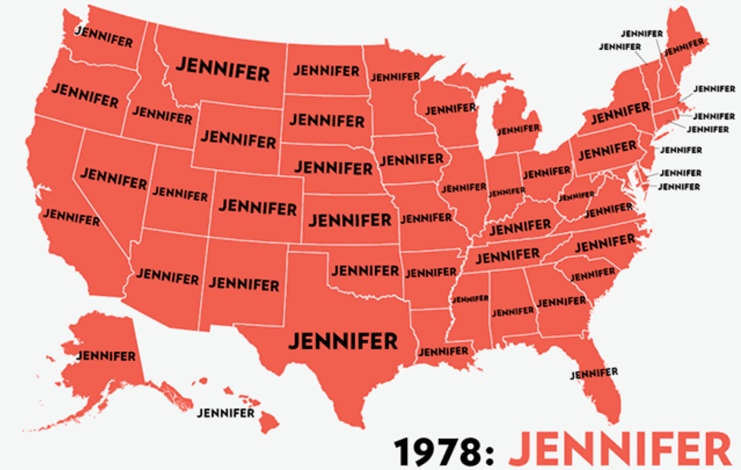

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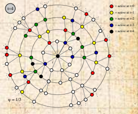

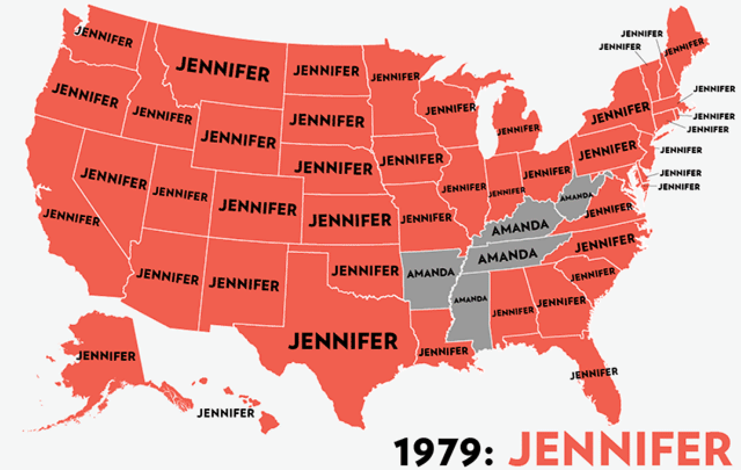

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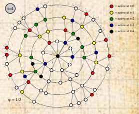

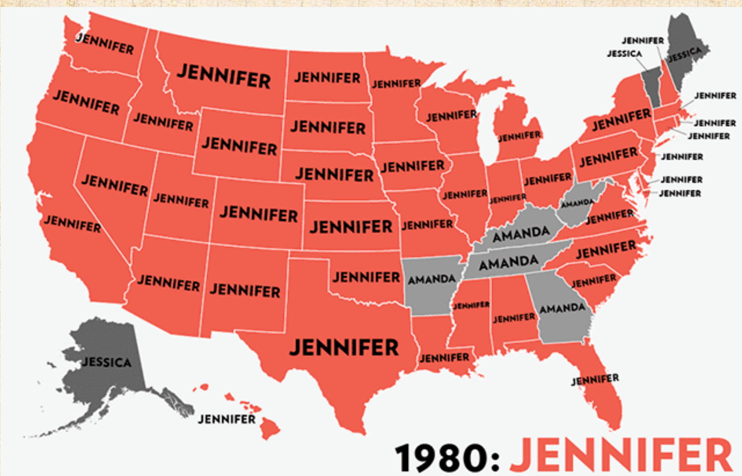

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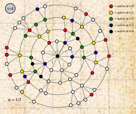

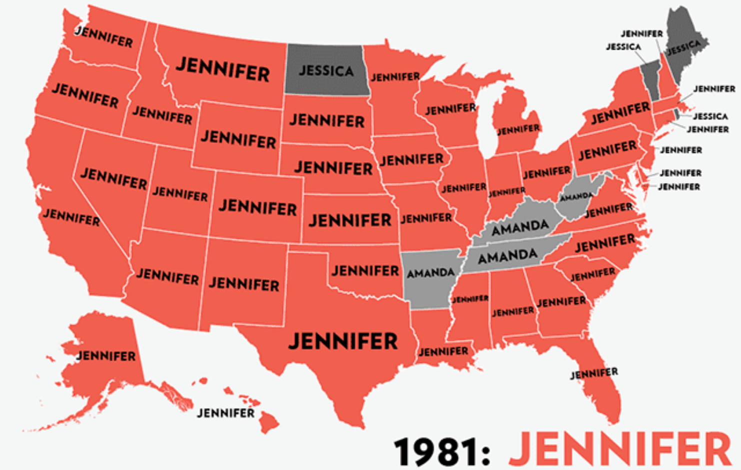

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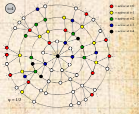

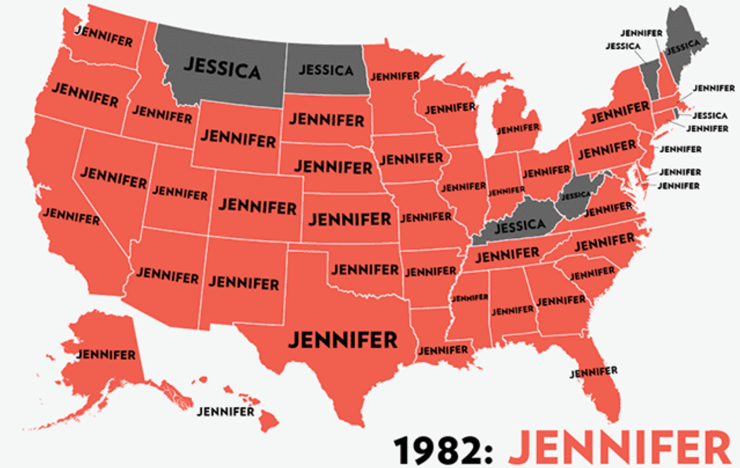

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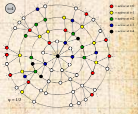

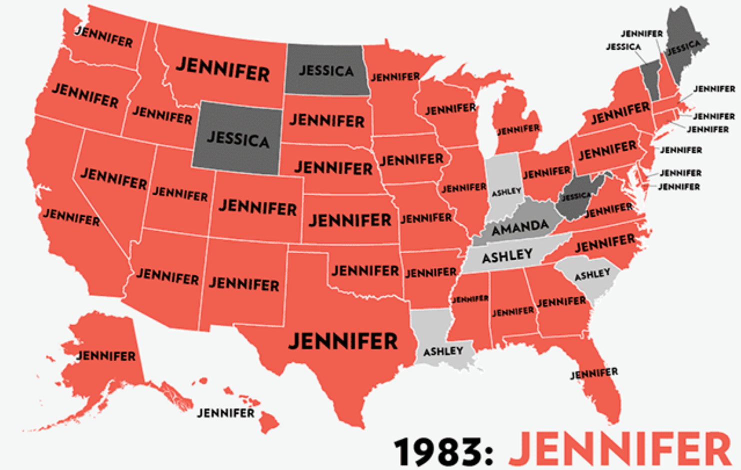

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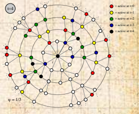

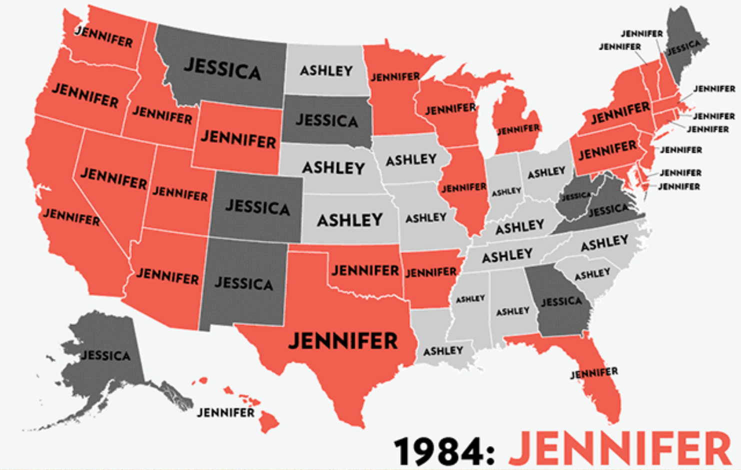

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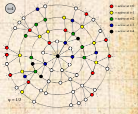

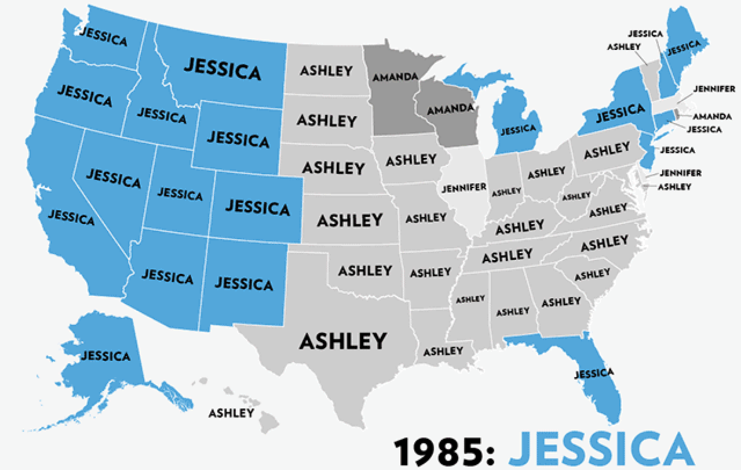

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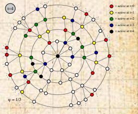

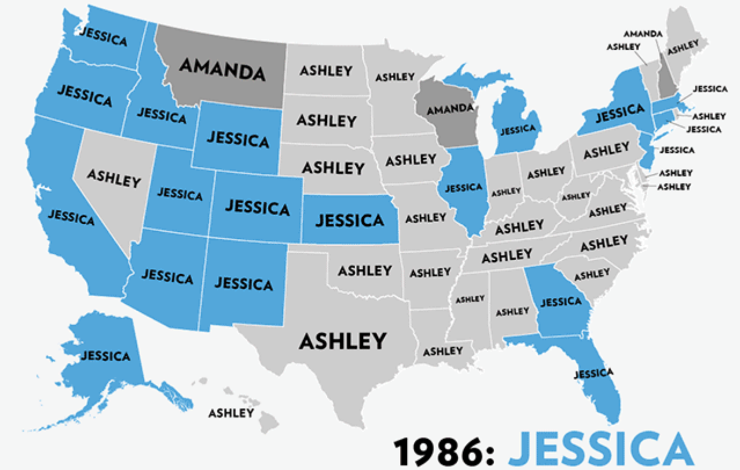

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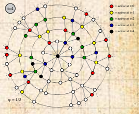

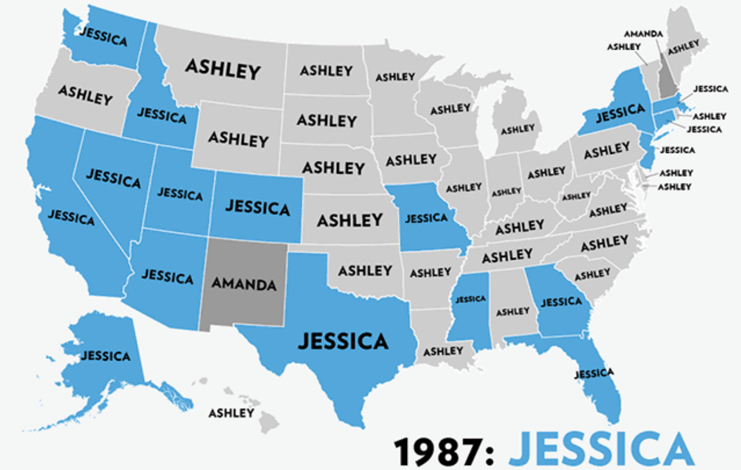

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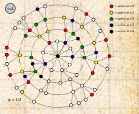

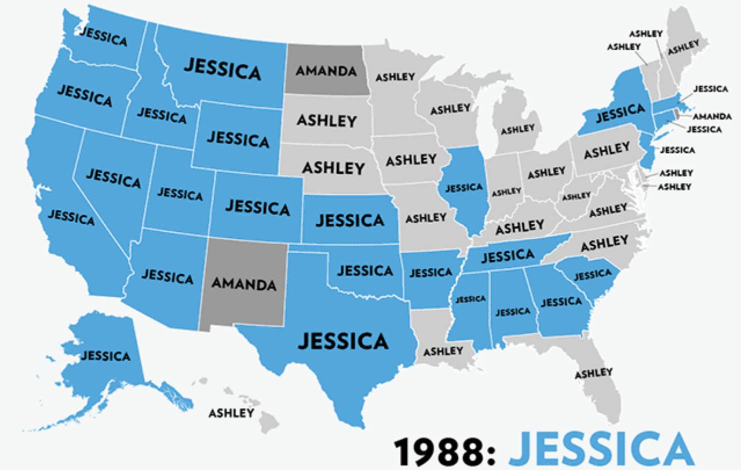

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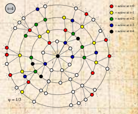

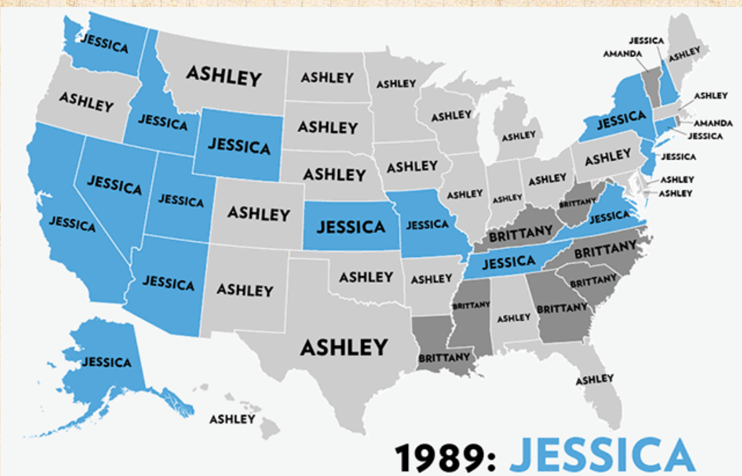

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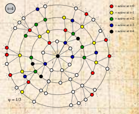

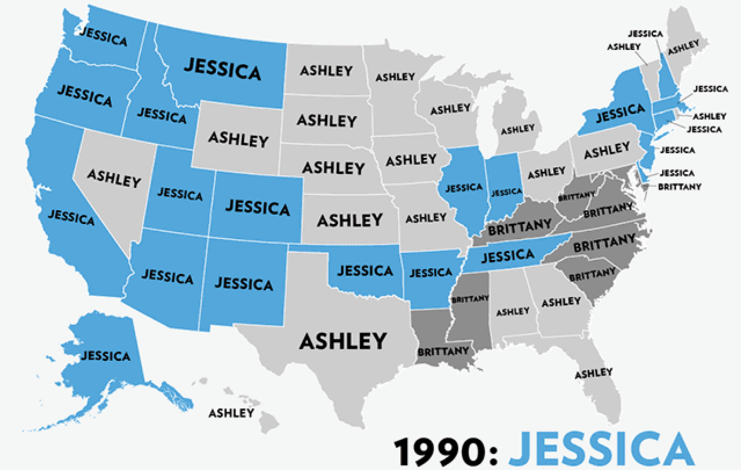

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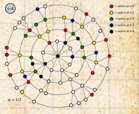

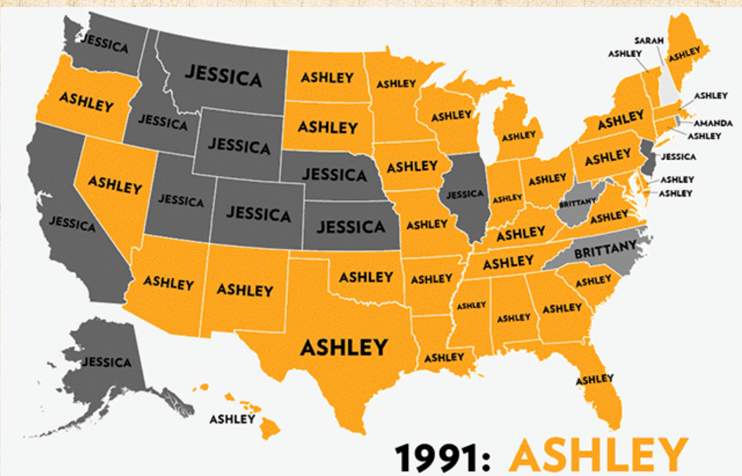

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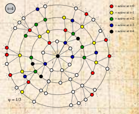

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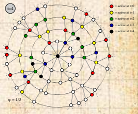

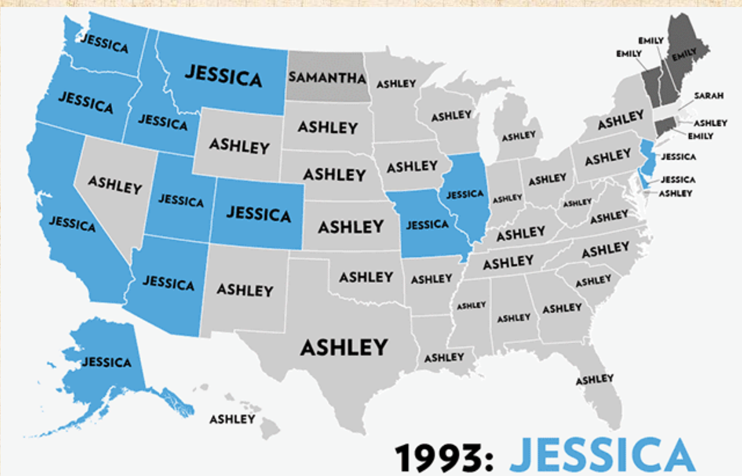

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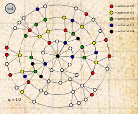

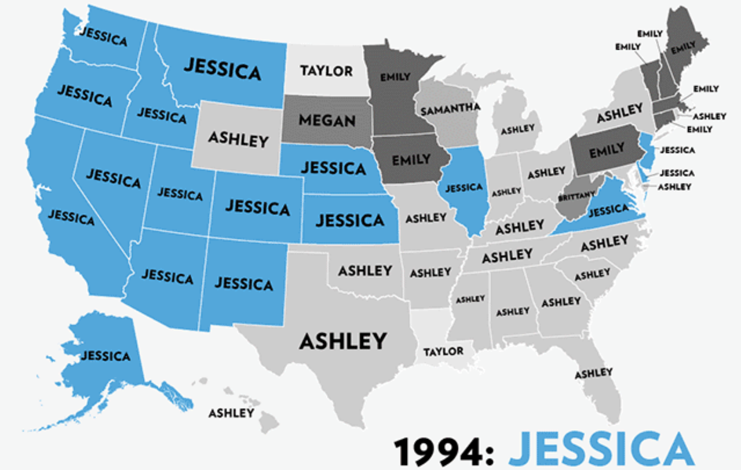

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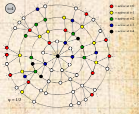

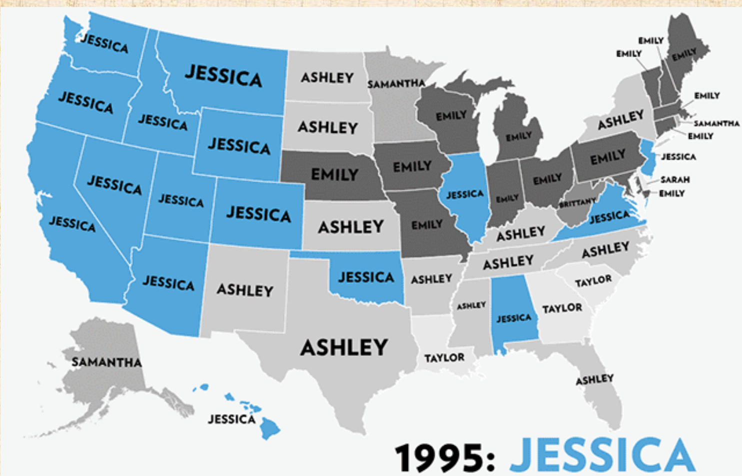

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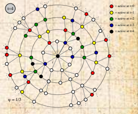

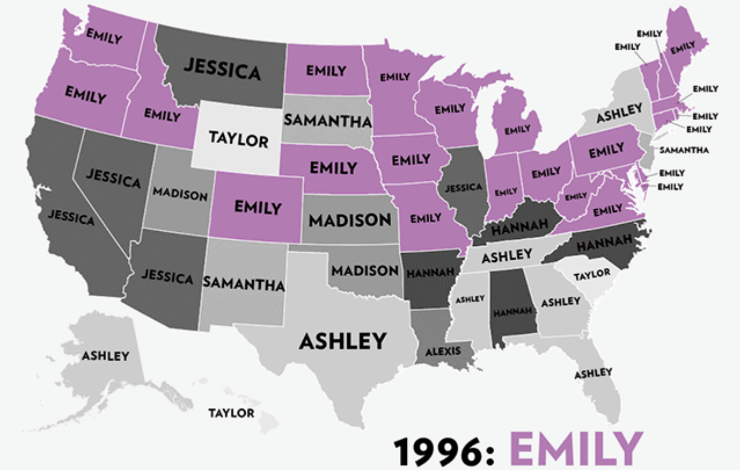

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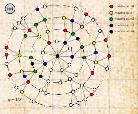

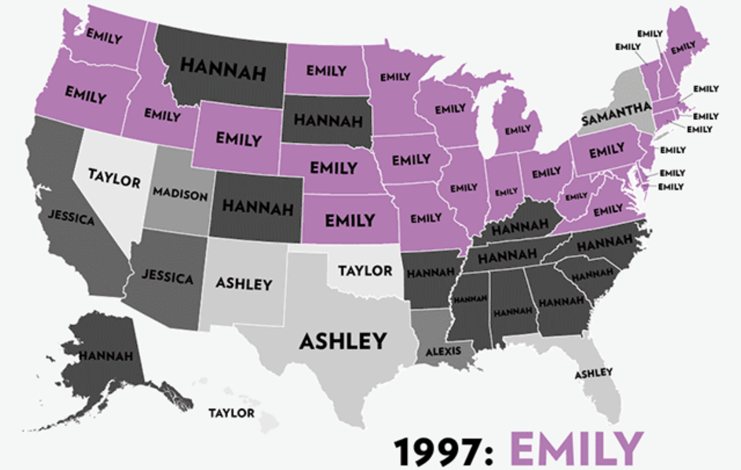

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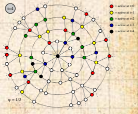

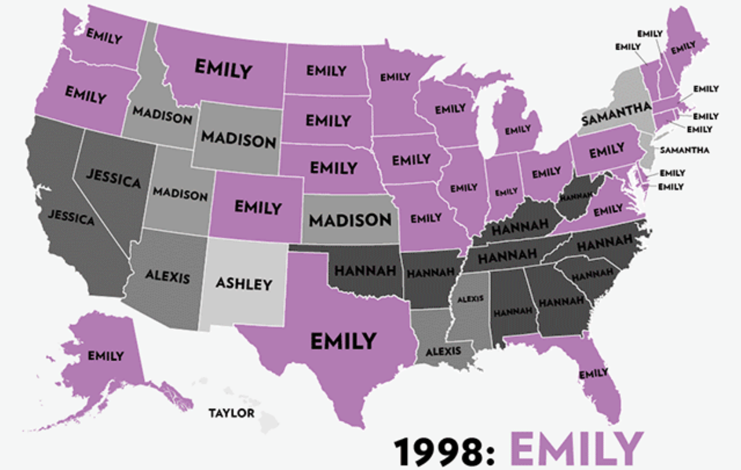

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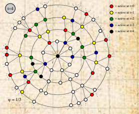

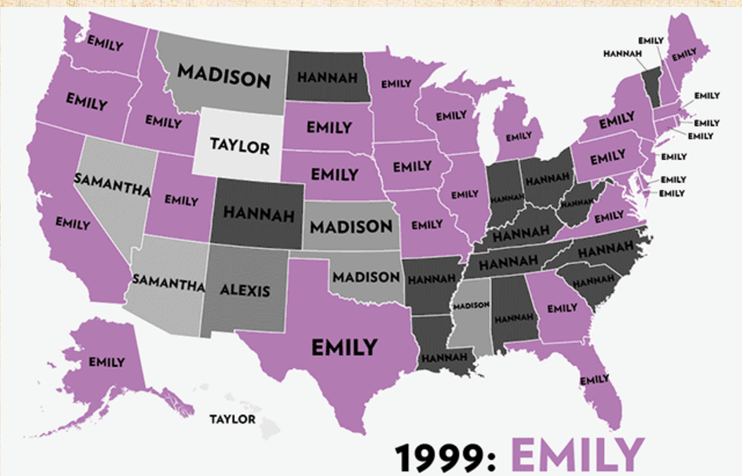

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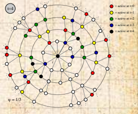

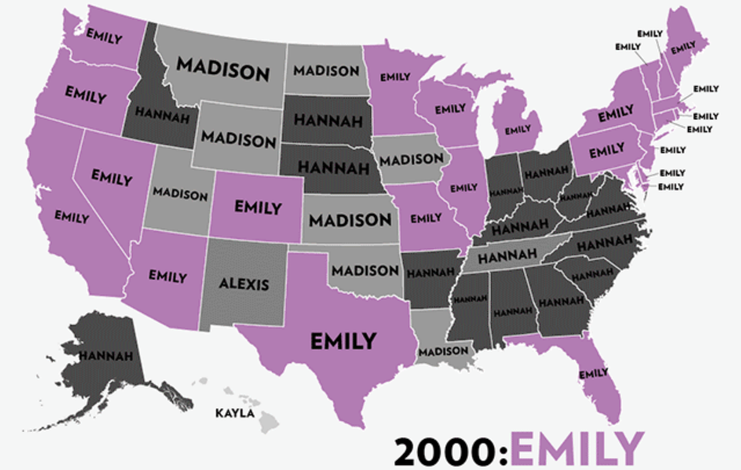

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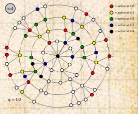

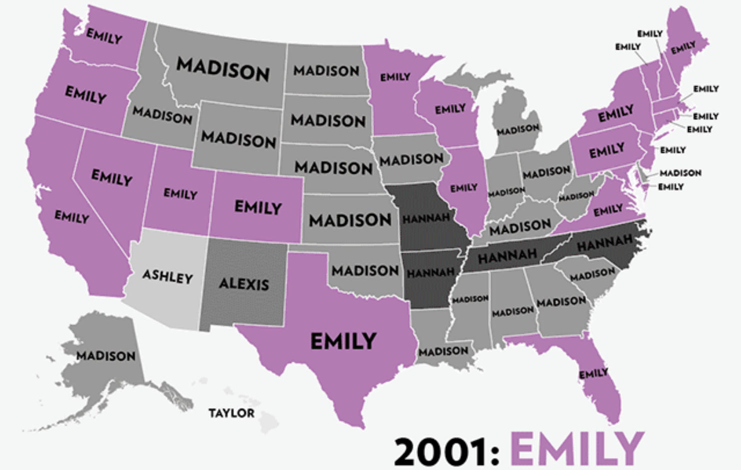

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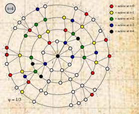

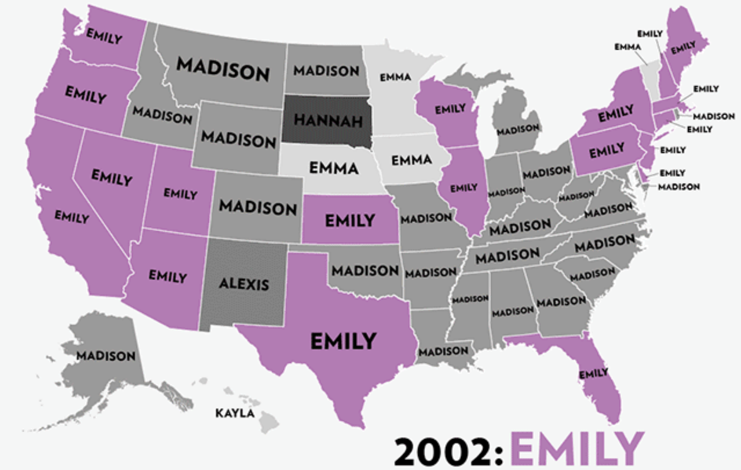

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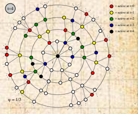

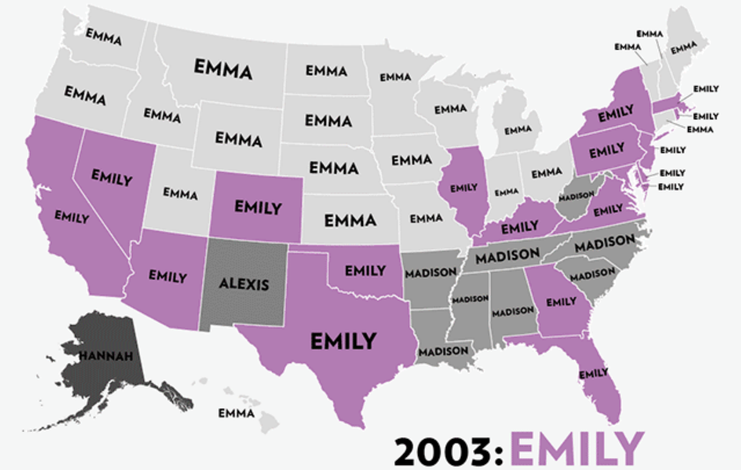

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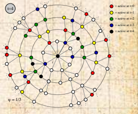

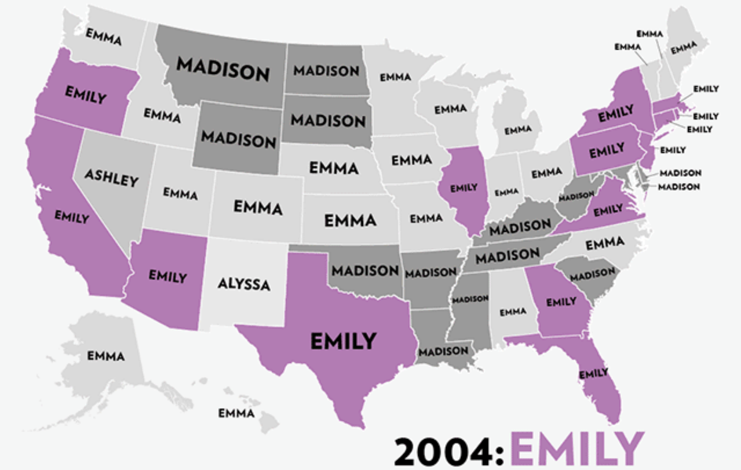

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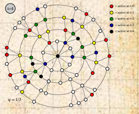

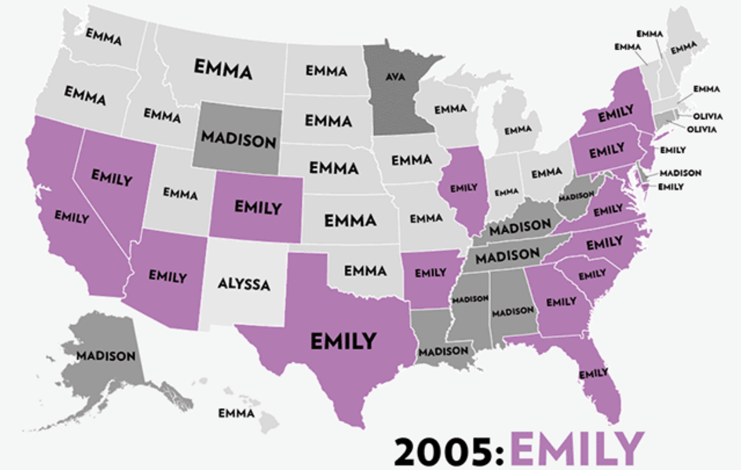

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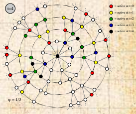

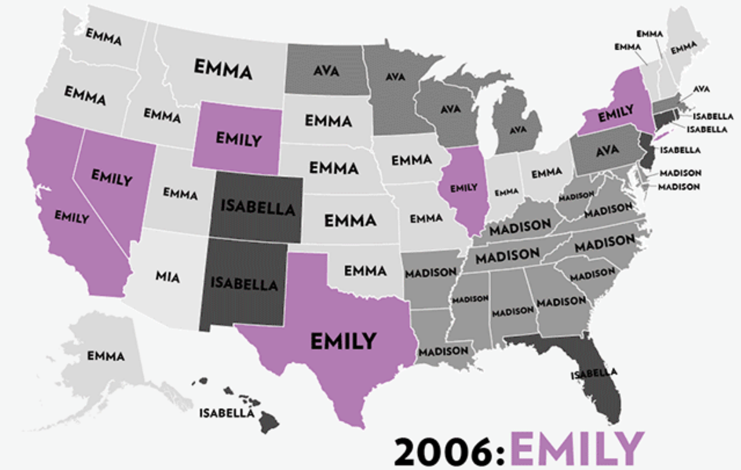

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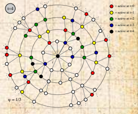

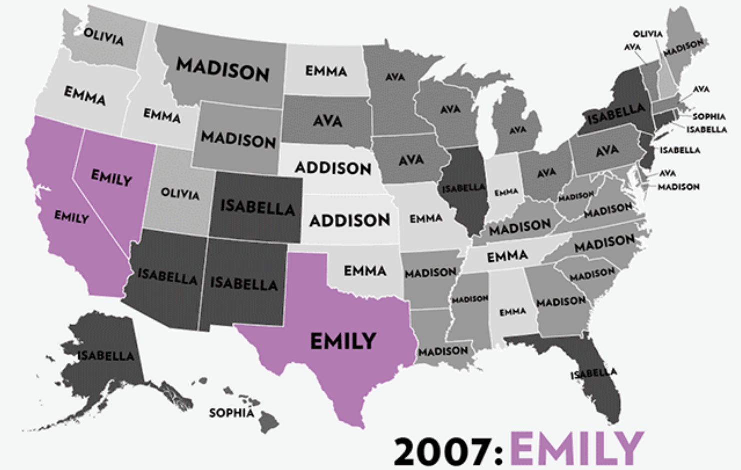

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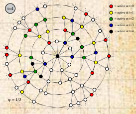

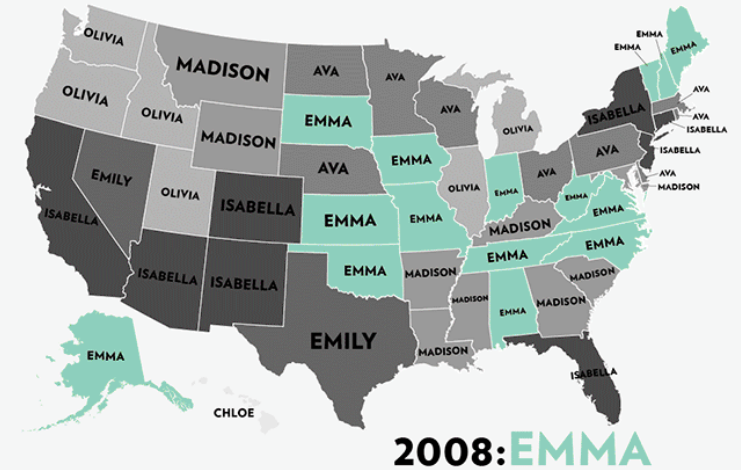

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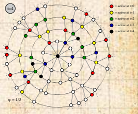

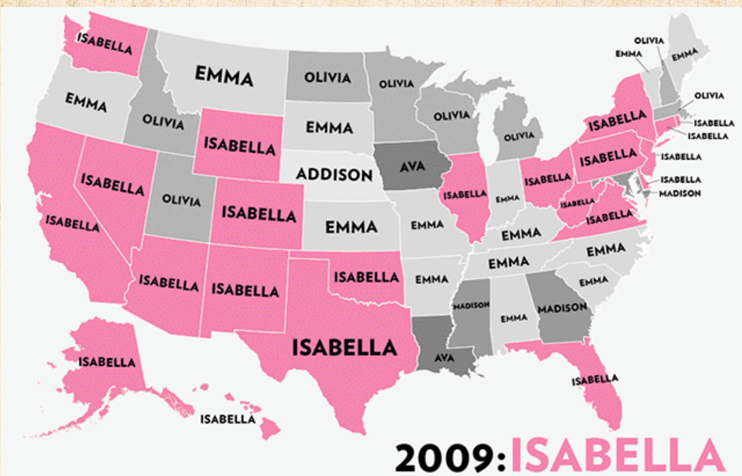

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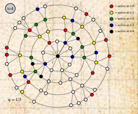

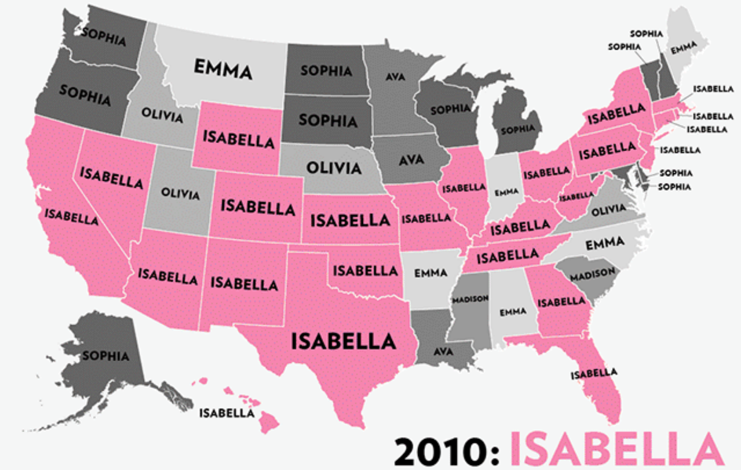

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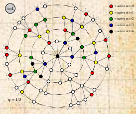

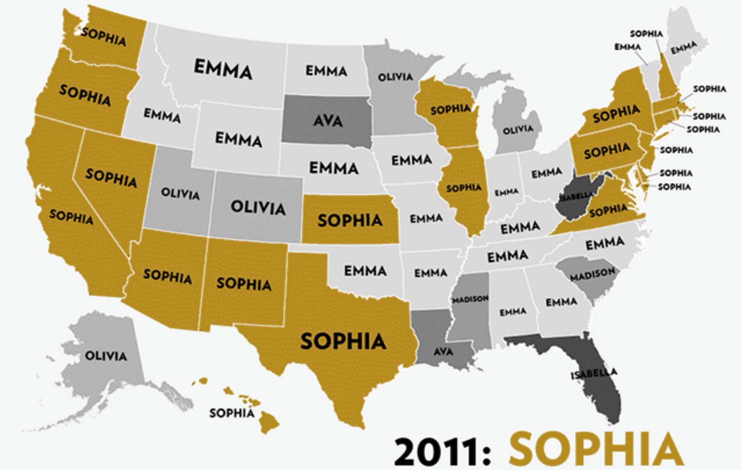

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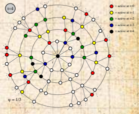

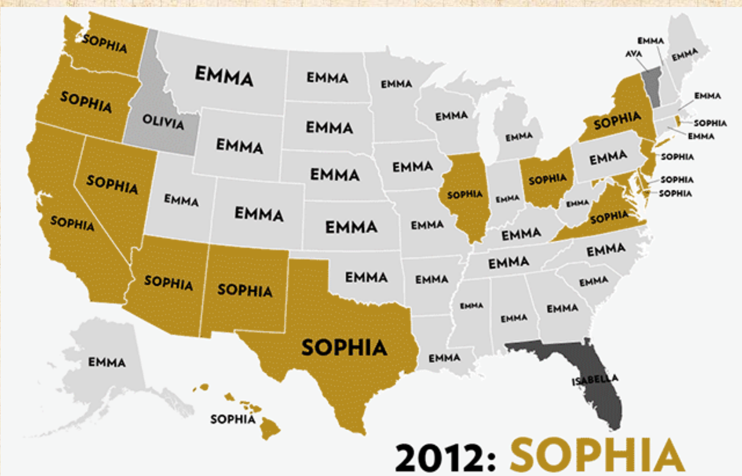

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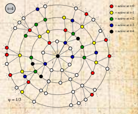
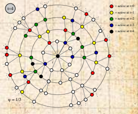
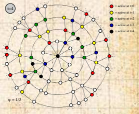


Richard Feynmann on the Social Sciences:



Sheldon Cooper on the Social Sciences:

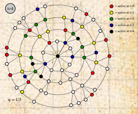


Things that spread well:

buzzfeed.com:

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

+ News ...



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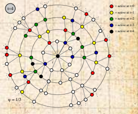
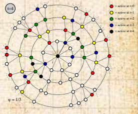
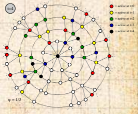


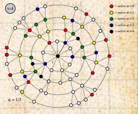
LOL + cute + fail + wtf:



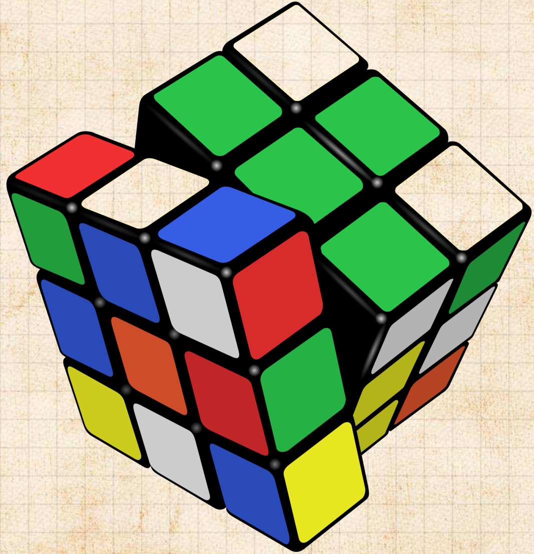
The whole lolcats thing:

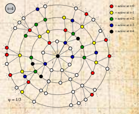


Some things really stick:

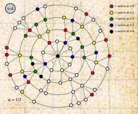


wtf + geeky + omg:

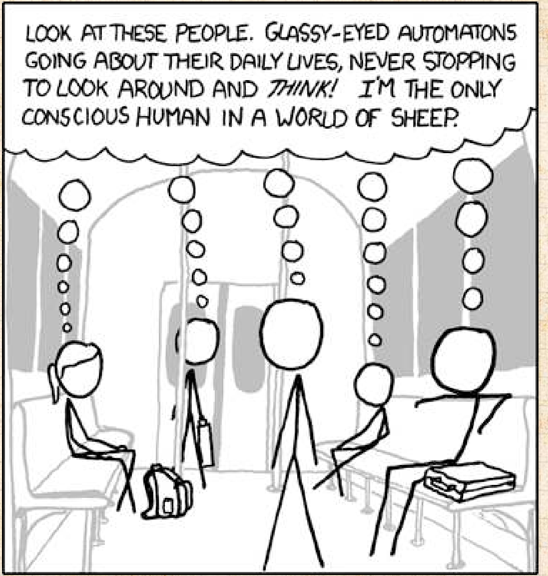




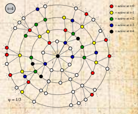
Outline



Why social contagion works so well:



http://xkcd.com/610/



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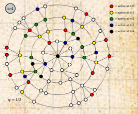


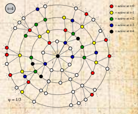
Social Contagion

Examples abound

- fashion
- striking
- smoking [7]
- residential segregation [22]
- iPhones and iThings
- obesity [6]
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- school shootings
- leaving lectures

SIR and SIRS type contagion possible

- Classes of behavior versus specific behavior



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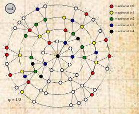

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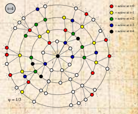

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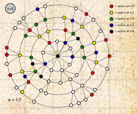
SIR and SIRS type contagion possible

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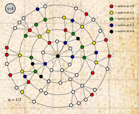
- In Stranger Things 2, Steve Harrington reveals his Fabergé secret.



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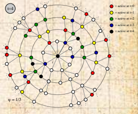

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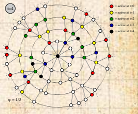
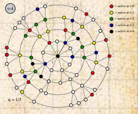


Market much?

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]
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- Also: happiness [11], loneliness, ...
- The book: Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives

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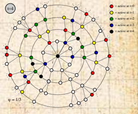

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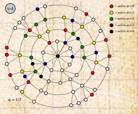

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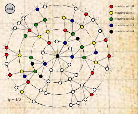

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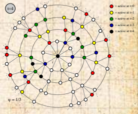

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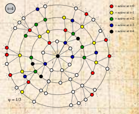


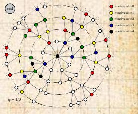
Social Contagion

Two focuses for us

- Widespread media influence
- Word-of-mouth influence

We need to understand influence

- Who influences whom?
- What kinds of influence response functions are there?
- Are some individuals super influencers?
- The infectious idea of opinion leaders (Katz and Lazarsfeld)[19]



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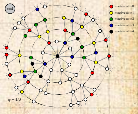

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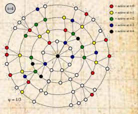

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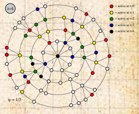

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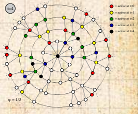

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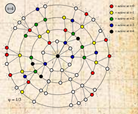

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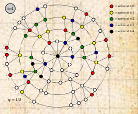

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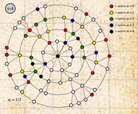

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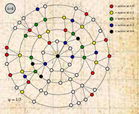

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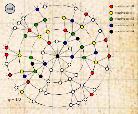
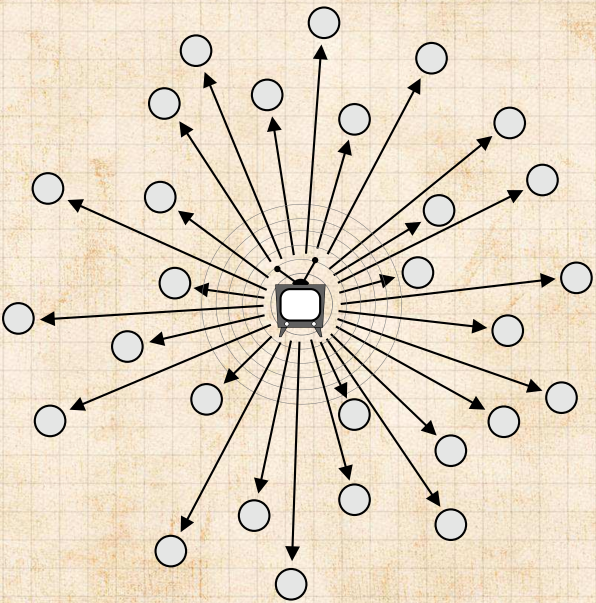
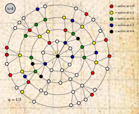
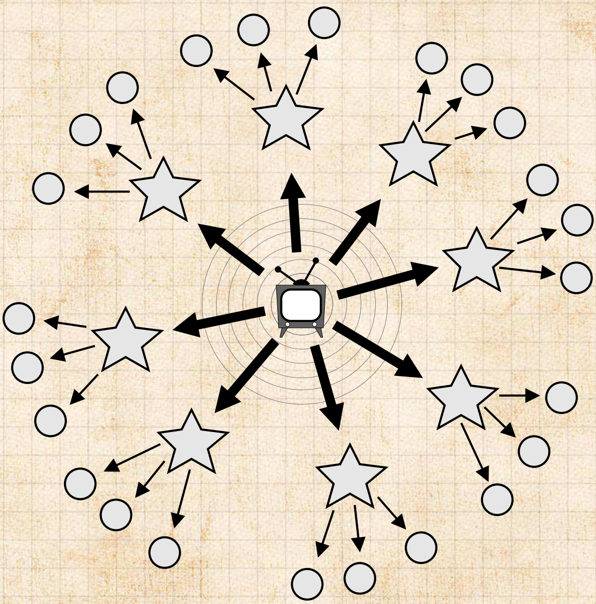


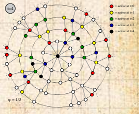
The hypodermic model of influence



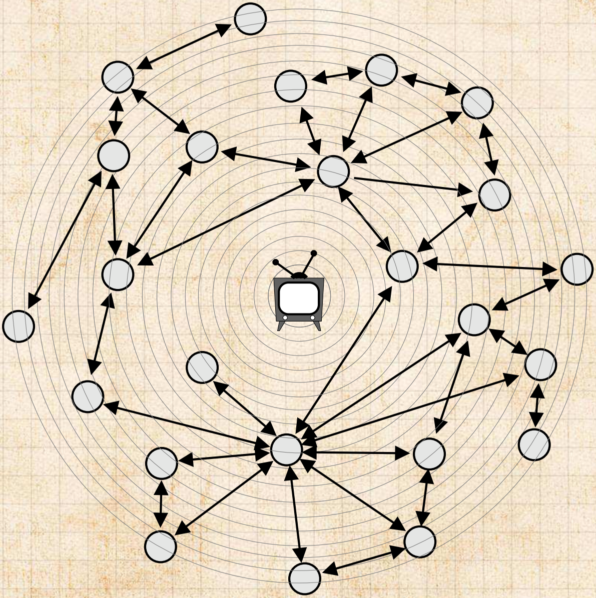


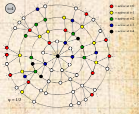
The two step model of influence [19]



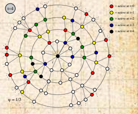


The general model of influence: the Social Wild



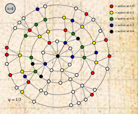


Talking about the social wild:



Why do things spread socially?

- Because of properties of special individuals?
- Or system level properties?
- Is the match that lights the fire important?
- Yes. But only because we are storytellers: *homo narrativus* ↗.
- We like to think things happened for reasons ...
- Reasons for success are usually ascribed to intrinsic properties (examples next).
- Teleological stories of fame are often easy to generate and believe.
- System/group dynamics harder to understand because most of our stories are built around individuals.
- Always good to examine what is said before and after the fact ...



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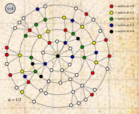

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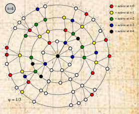

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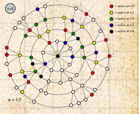

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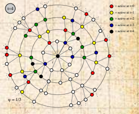

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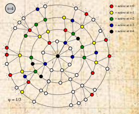

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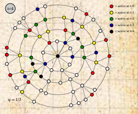

Why do things spread socially?

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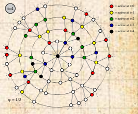

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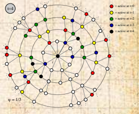

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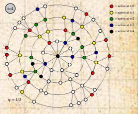

The Mona Lisa

- "Becoming Mona Lisa: The Making of a Global Icon"—David Sassoon
- Not the world's greatest painting from the start...
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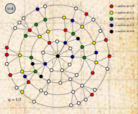

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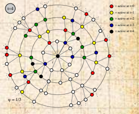

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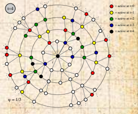

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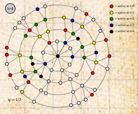

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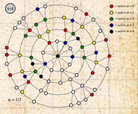
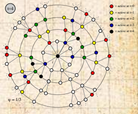


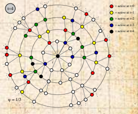
'Tattooed Guy' Was Pivotal in Armstrong Case [nytimes]

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

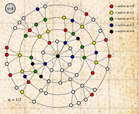


The completely unpredicted fall of Eastern Europe:

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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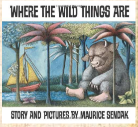

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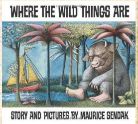

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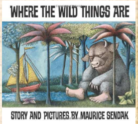

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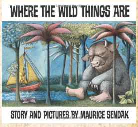

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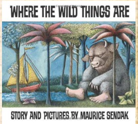

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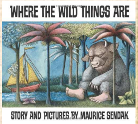

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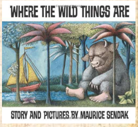

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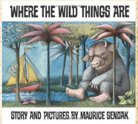

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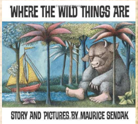

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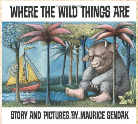

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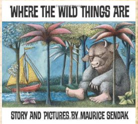

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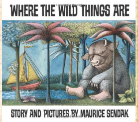

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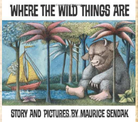

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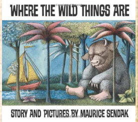

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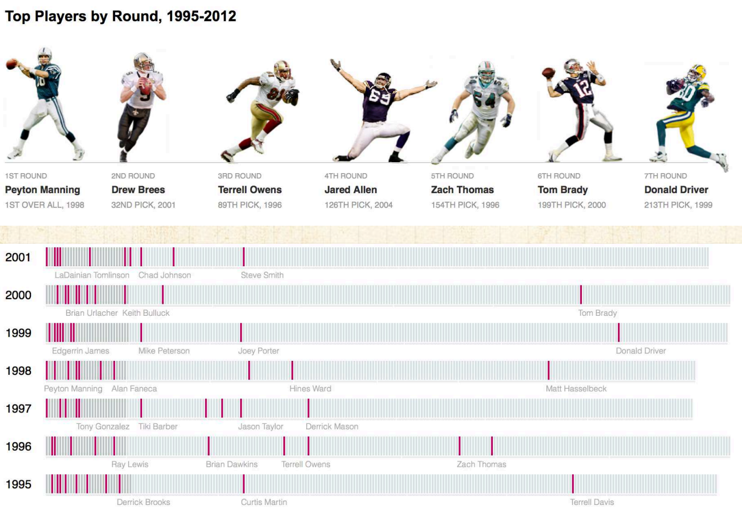

Social Contagion

Messing with social connections

- Ads based on message content
- BzzAgent
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  - Generally: BzzAgents did not reveal their BzzAgent status and did not want to be paid.
  - NYT, 2004-12-05: "The Hidden (in Plain Sight) Persuaders"
- One of Facebook's early advertising attempts: Beacon
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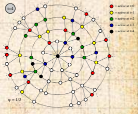

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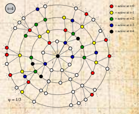

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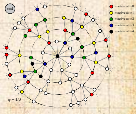

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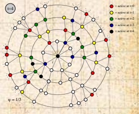

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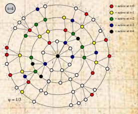

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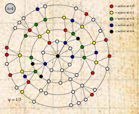

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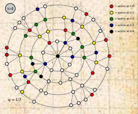

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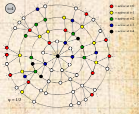

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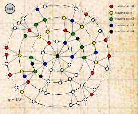

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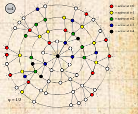

Getting others to do things for you

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.
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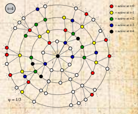

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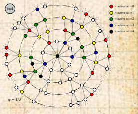

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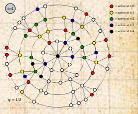

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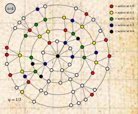

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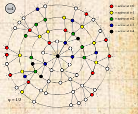

Social contagion

- Cialdini's modes are heuristics that help up us get through life.
- Useful but can be leveraged...

Other acts of influence:

- Conspicuous Consumption (Veblen, 1912)
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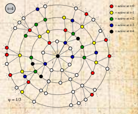

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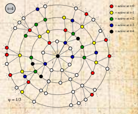

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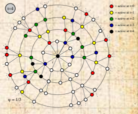

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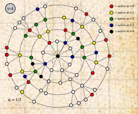

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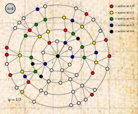

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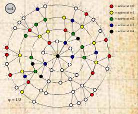

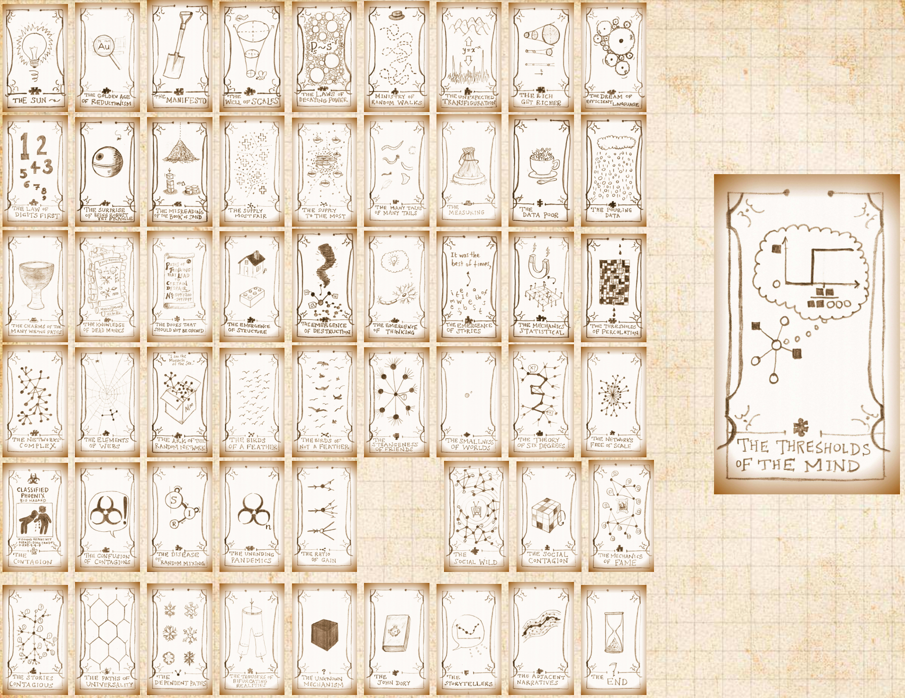

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THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE LAW OF DIGITS FIRST
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE SUPPLY MOST FAIR
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THE MANY TALES OF MANY TAILS
THE MEASURING
THE DATA POOR
THE POURING DATA
THE CHARMS OF THE MANY WRONG PATHS
THE KNOWLEDGE OF DEAD MONKS
THE DOORS THAT SHOULD NOT BE OPENED
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THE EMERGENCE OF THINKING
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THE NETWORKS COMPLEX
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THE MECHANICS OF FAME
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Social Contagion

Some important models:

- Tipping models—Schelling (1971) [22, 23, 24]
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  - Idea of thresholds
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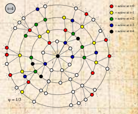

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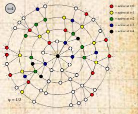

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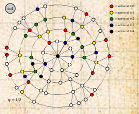

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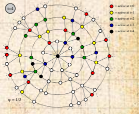

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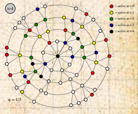

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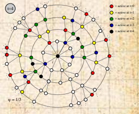

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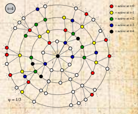

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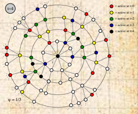

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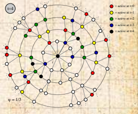
Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform



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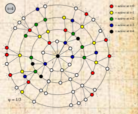

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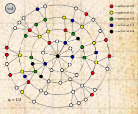

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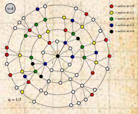

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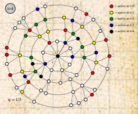

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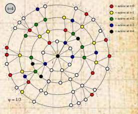

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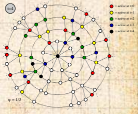

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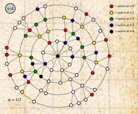

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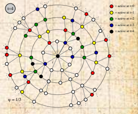

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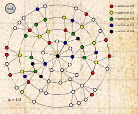
Some possible origins of thresholds:

- Inherent, evolution-devised inclination to coordinate, to conform, to imitate.[1]
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
  - Externalities = Effects on others not directly involved in a transaction
  - Examples: telephones, fax machine, Facebook, operating systems
  - An individual's utility increases with the adoption level among peers and the population in general



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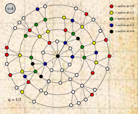

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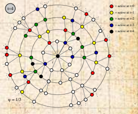

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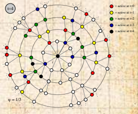

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- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
  - Externalities = Effects on others not directly involved in a transaction
  - Examples: telephones, fax machine, Facebook, operating systems
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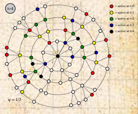

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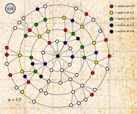

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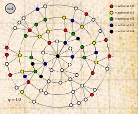
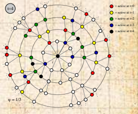


Neural reboot (NR):

Shareworthy interlude

https://www.youtube.com/watch?v=LL2GQrvbb1k?rel=0



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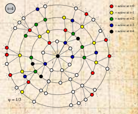
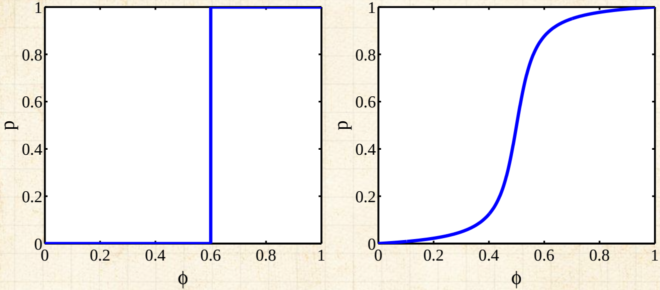
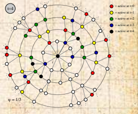


Threshold models—response functions



- Example threshold influence response functions: deterministic and stochastic
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Two states: S and I.



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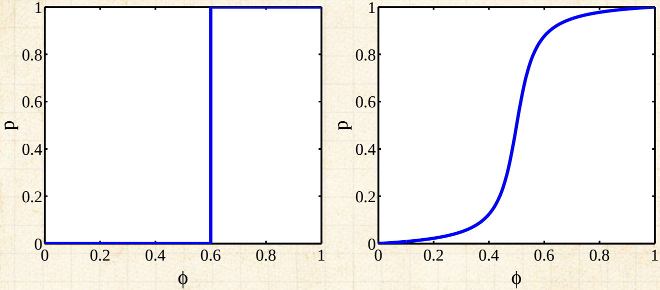

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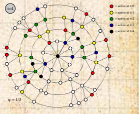

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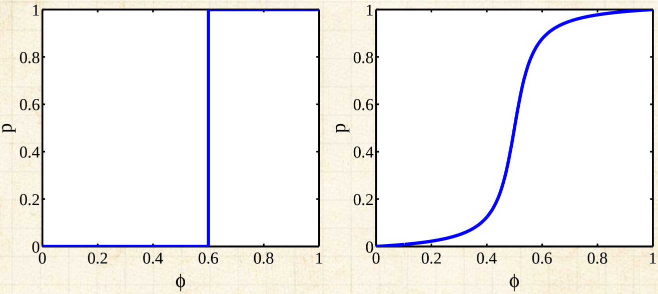

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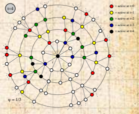
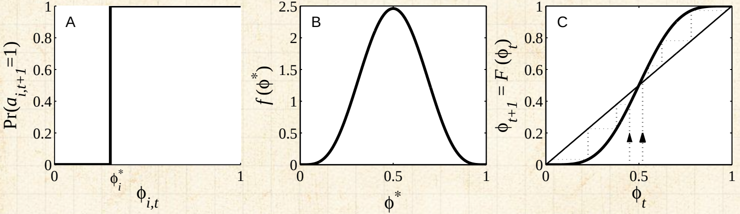


Threshold models

Action based on perceived behavior of others:



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- Discrete time update (strong assumption!)
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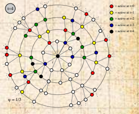

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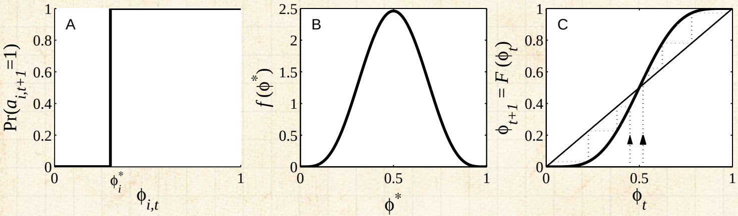

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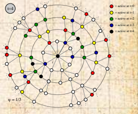

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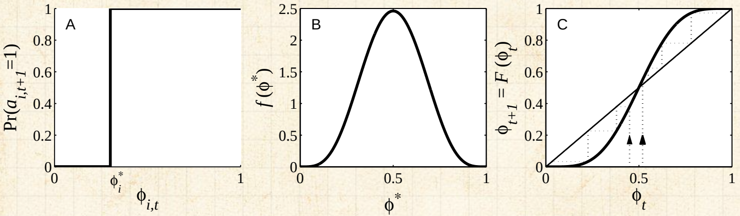

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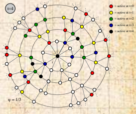
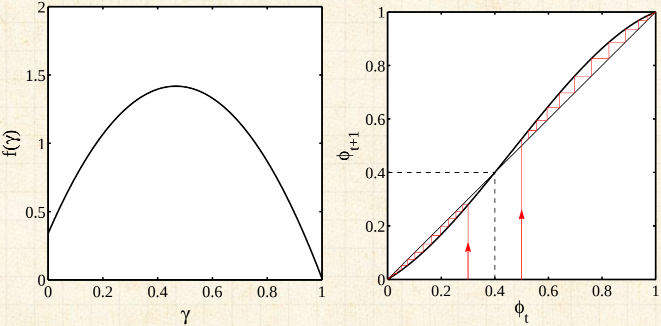
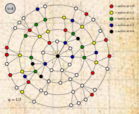


Threshold models

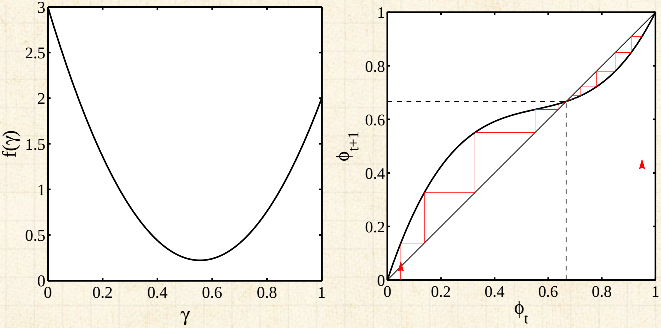
Another example of critical mass model:

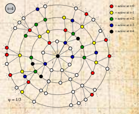




Threshold models

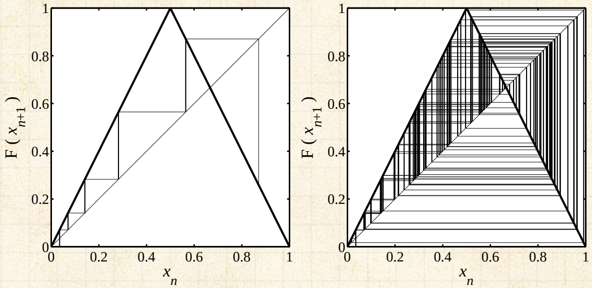
Example of single stable state model:



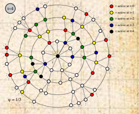


Threshold models

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



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



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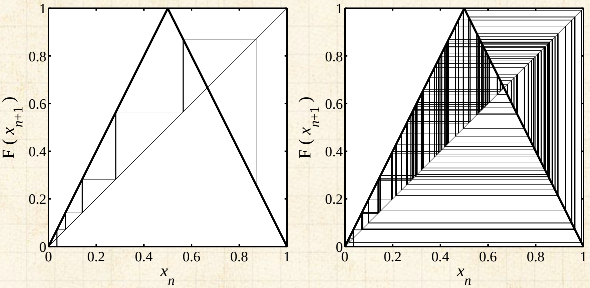

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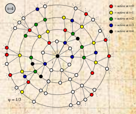

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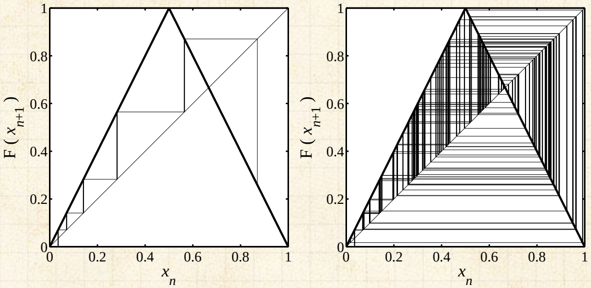

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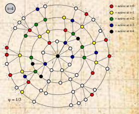
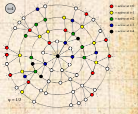


Threshold models—Nutshell

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.



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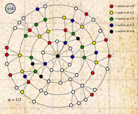

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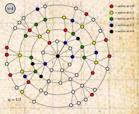

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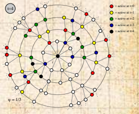

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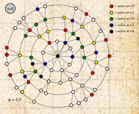

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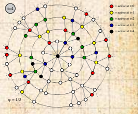

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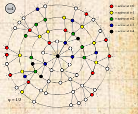

Many years after Granovetter and Soong's work:

- "A simple model of global cascades on random networks"
  D. J. Watts. Proc. Natl. Acad. Sci., 2002 [26]
  - Mean field model → network model
  - Individuals now have a limited view of the world

We'll also explore:

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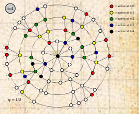

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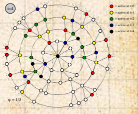

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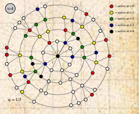

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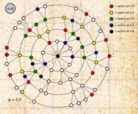
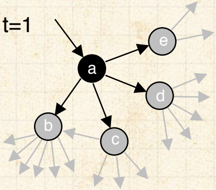
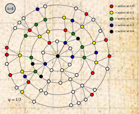


Threshold model on a network



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



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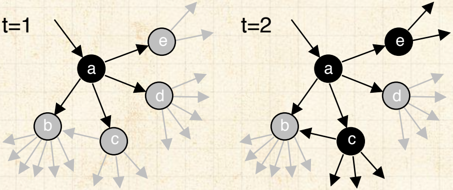

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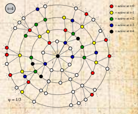

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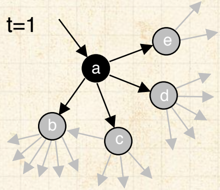

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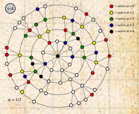
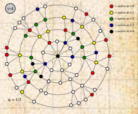


Threshold model on a network

- Interactions between individuals now represented by a network.
- Network is sparse.
- Individual i has k_i contacts.
- Influence on each link is reciprocal and of unit weight.
- Each individual i has a fixed threshold ϕ_i.
- Individuals repeatedly poll contacts on network.
- Synchronous, discrete time updating.
- Individual i becomes active when fraction of active contacts $\frac{a_i}{k_i} \geq \phi_i$.
- Individuals remain active when switched (no recovery = SI model).



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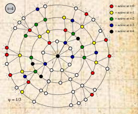

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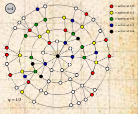

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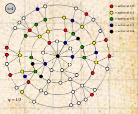

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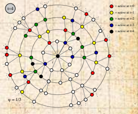

Threshold model on a network

- Interactions between individuals now represented by a network.
- Network is sparse.
- Individual i has k_i contacts.
- Influence on each link is reciprocal and of unit weight.
- Each individual i has a fixed threshold ϕ_i.
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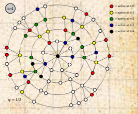

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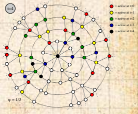

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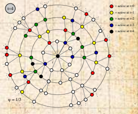

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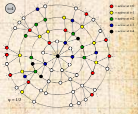


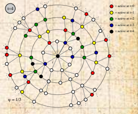
Snowballing

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

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?



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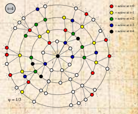

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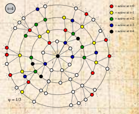

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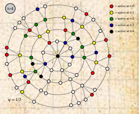

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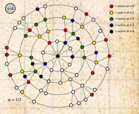

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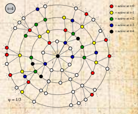

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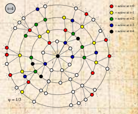
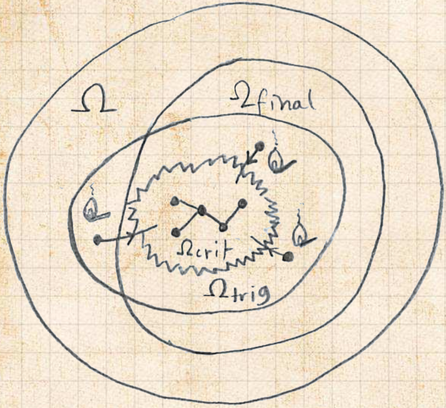
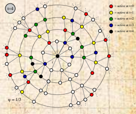


Example random network structure:



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

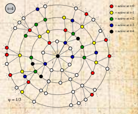
$\Omega_{\text{crit}} \subset \Omega_{\text{trig}};\ \Omega_{\text{crit}} \subset \Omega_{\text{final}};$ and $\Omega_{\text{trig}}, \Omega_{\text{final}} \subset \Omega.$



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.



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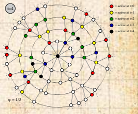

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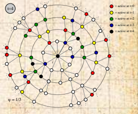

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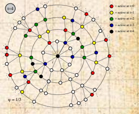

The most gullible

Vulnerables:

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

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
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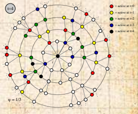
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.



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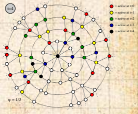

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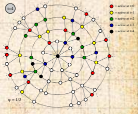

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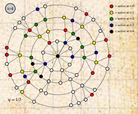

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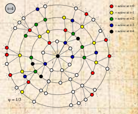

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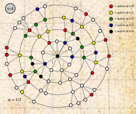

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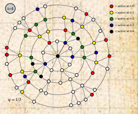


Cascade condition

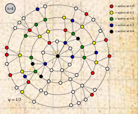
Back to following a link:

- A randomly chosen link, traversed in a random direction, leads to a degree k node with probability $\propto kP_k$.
- Follows from there being k ways to connect to a node with degree k.
- Normalization:

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

- So

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



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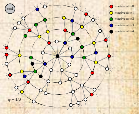

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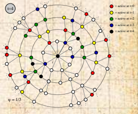

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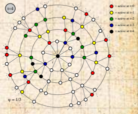

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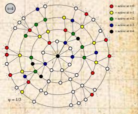


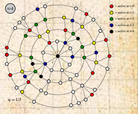
Cascade condition

Next: Vulnerability of linked node

- Linked node is vulnerable with probability

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

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



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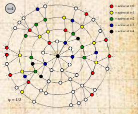

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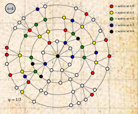

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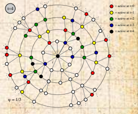

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Putting things together:

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

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

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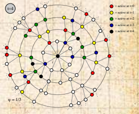

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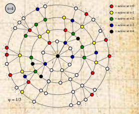

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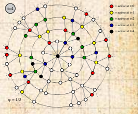

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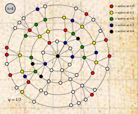
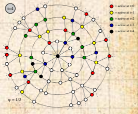


Cascade condition

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:

- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$

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

- (2) Giant component exists: $\beta = 1$

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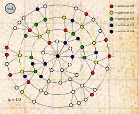

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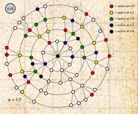

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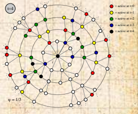

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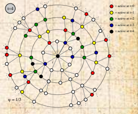

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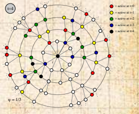
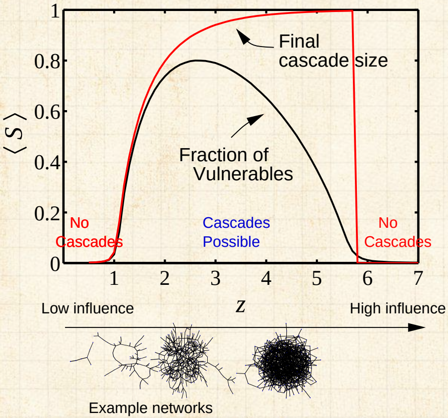
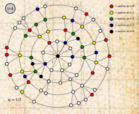


Cascades on random networks



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



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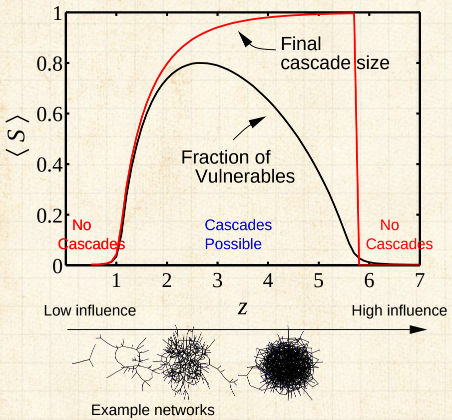

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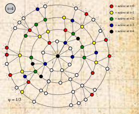

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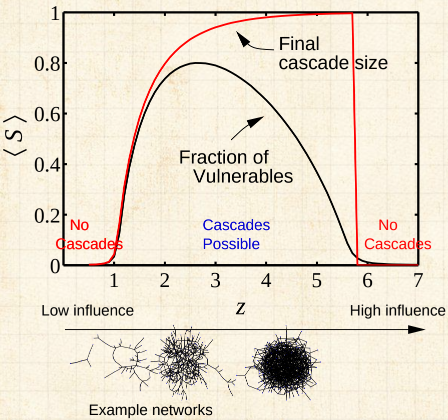

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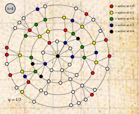
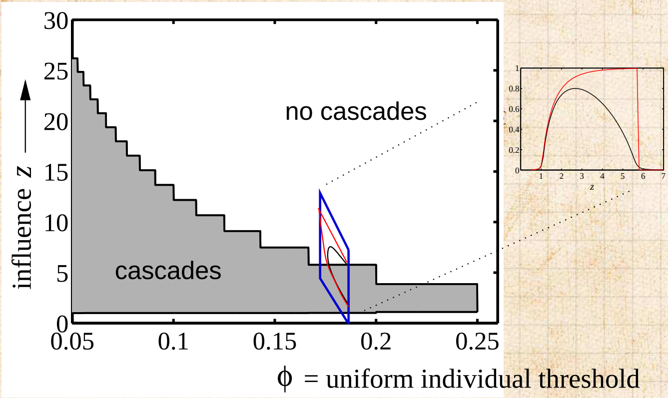
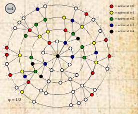


Cascade window for random networks



- 'Cascade window' widens as threshold ϕ decreases.
- Lower thresholds enable spreading.



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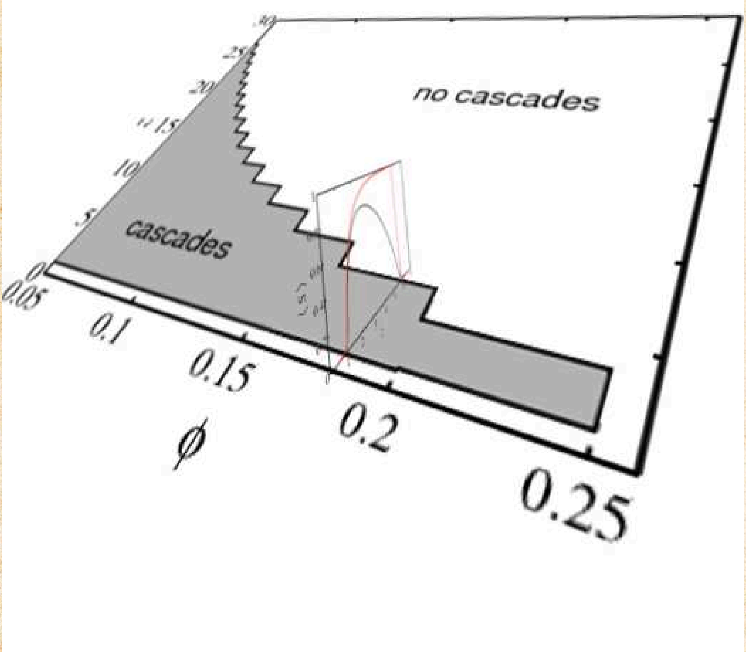
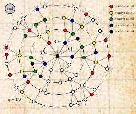
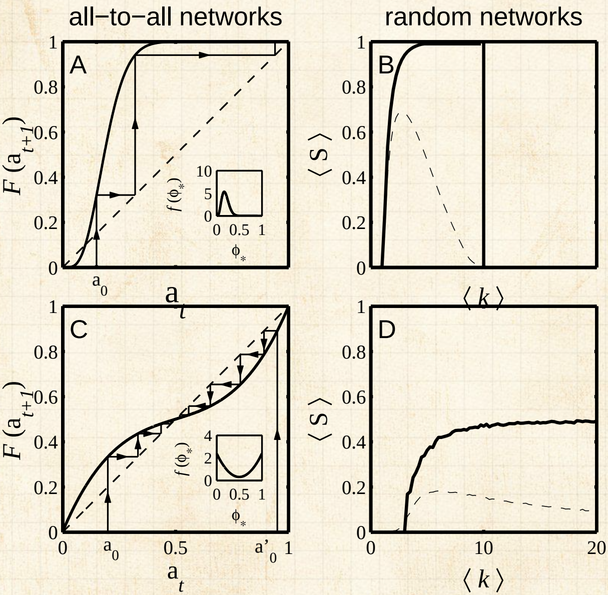
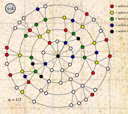




All-to-all versus random networks

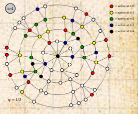




Cascade window—summary

For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks.
   No global clusters of any kind.
2. High $\langle k \rangle$: Giant component exists but not enough vulnerables.
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists.
   Cascades are possible in "Cascade window."



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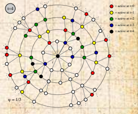

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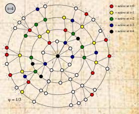

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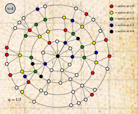
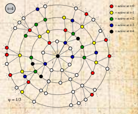


Outline



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 ≥ 2 hits switch on.
- Problem beautifully solved for infinite seed case by Gleeson and Cahalane:
  "Seed size strongly affects cascades on random networks," Phys. Rev. E, 2007.[14]
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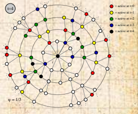

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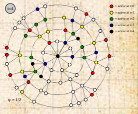

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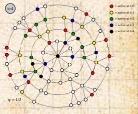

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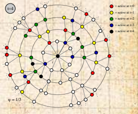

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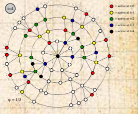

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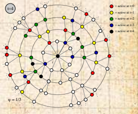

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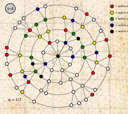

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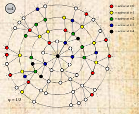

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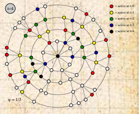

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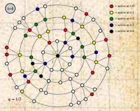

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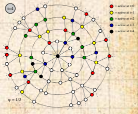

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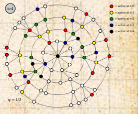

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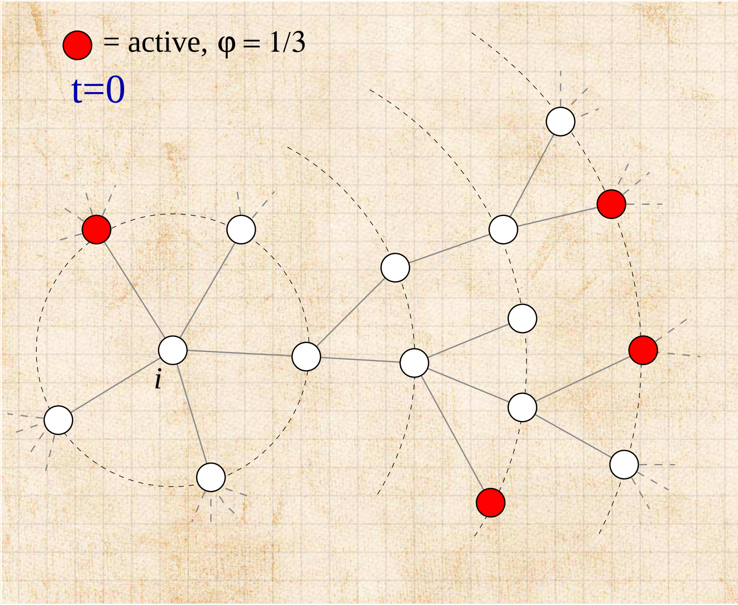

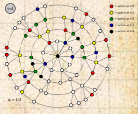

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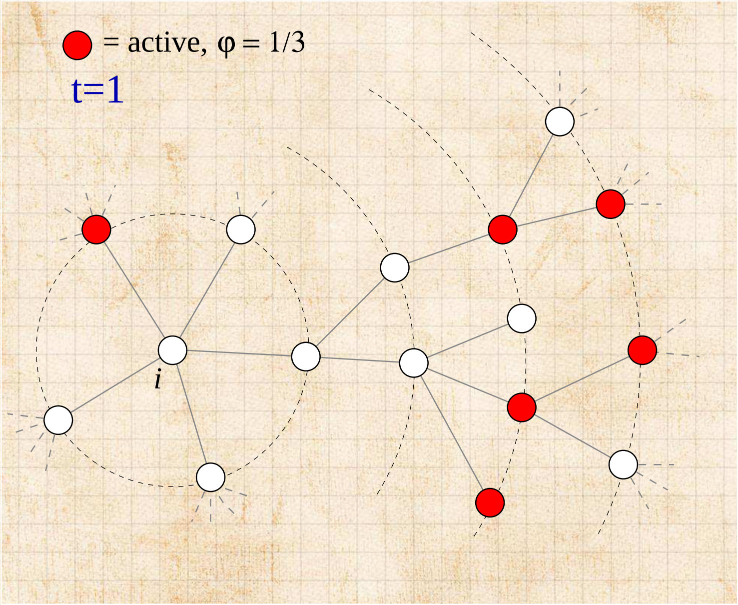

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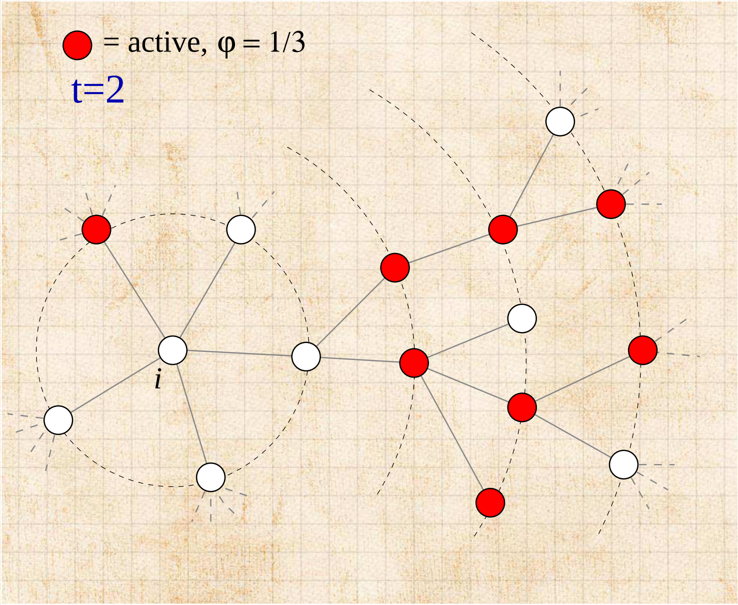

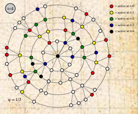

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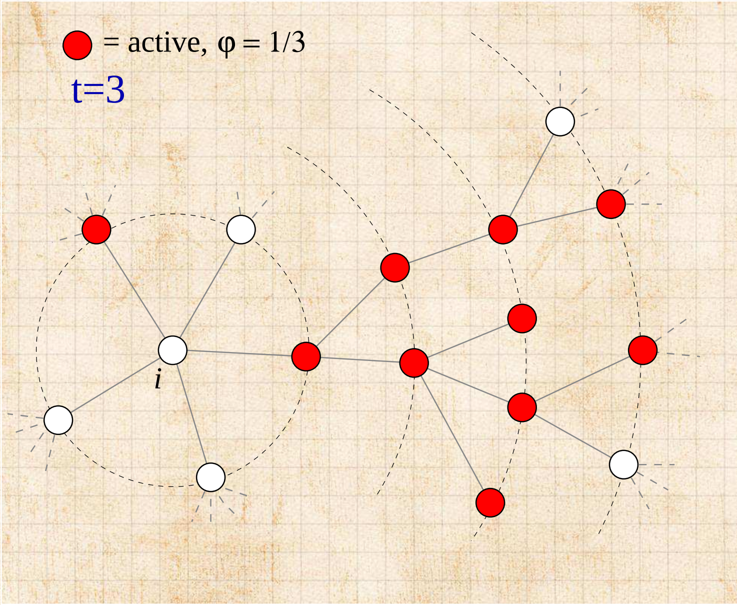

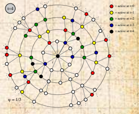

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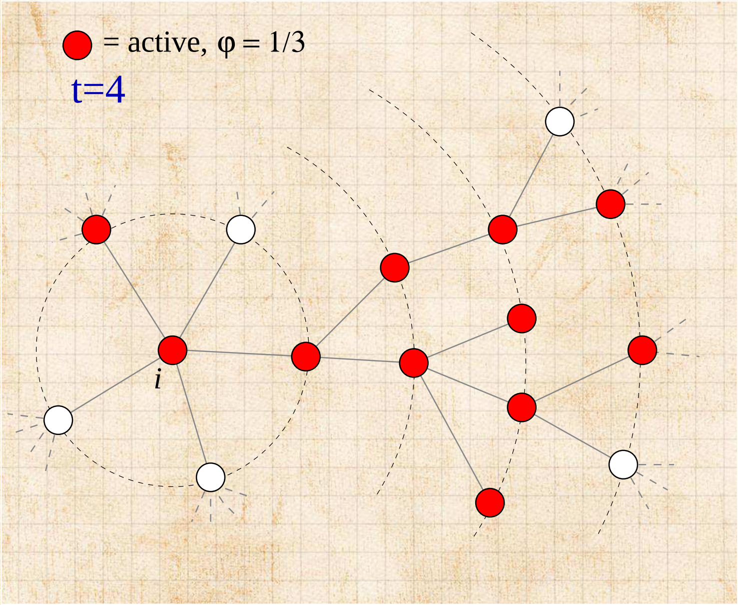

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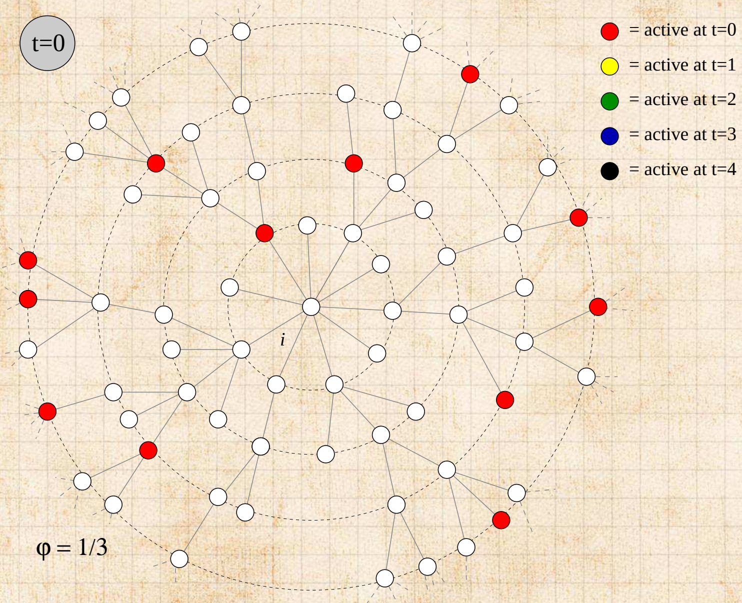

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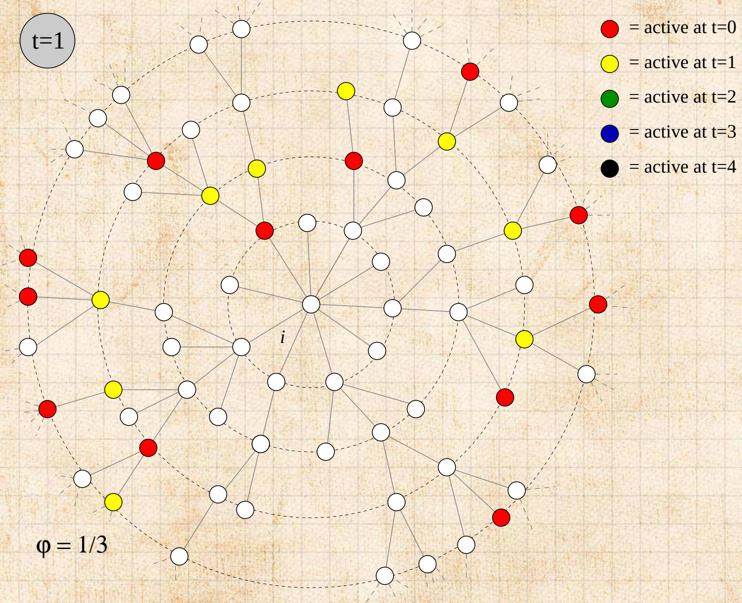

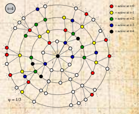

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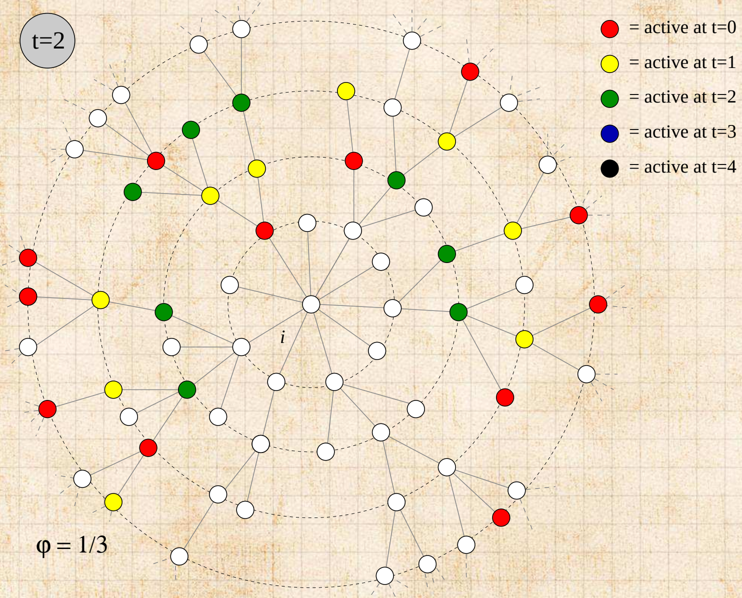

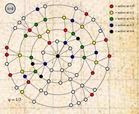

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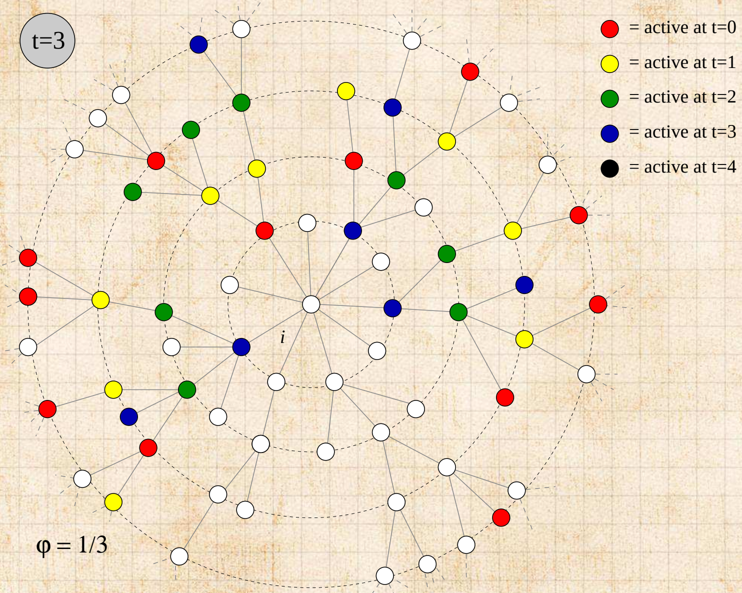

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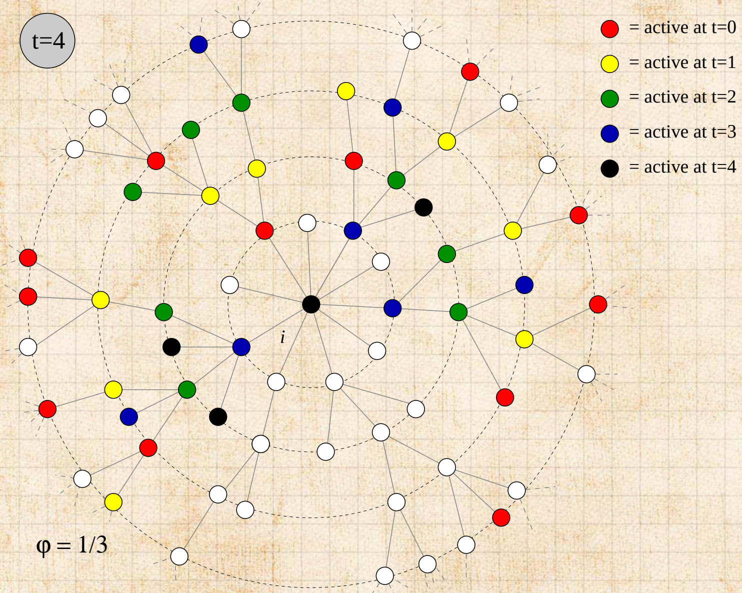

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Notes:

- Calculations are possible if nodes do not become inactive (strong restriction).
- Not just for threshold model—works for a wide range of contagion processes.
- We can analytically determine the entire time evolution, not just the final size.
- We can in fact determine **Pr**(node of degree k switching on at time t).
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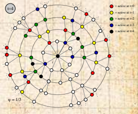

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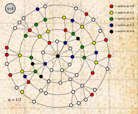

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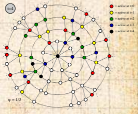

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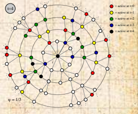

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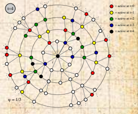
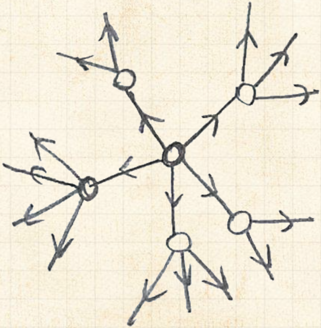
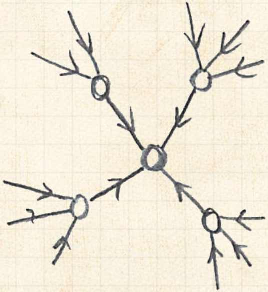


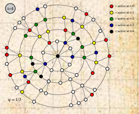
Expected size of spread

Pleasantness:

- Taking off from a single seed story is about expansion away from a node.
- Extent of spreading story is about contraction at a node.







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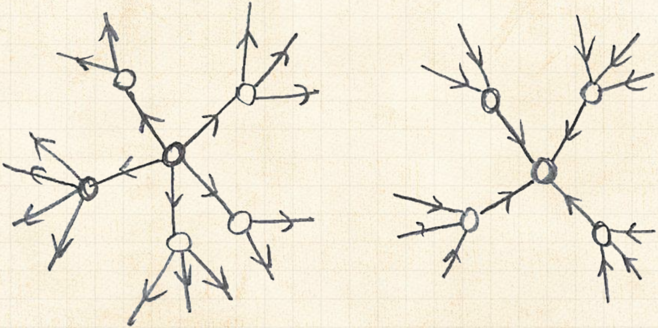

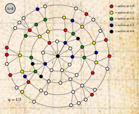

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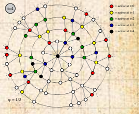

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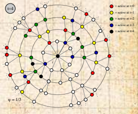

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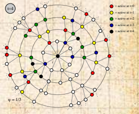

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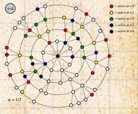

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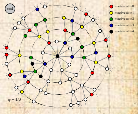

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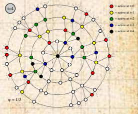

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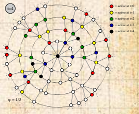

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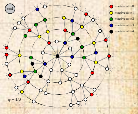

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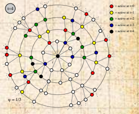

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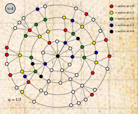

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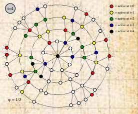

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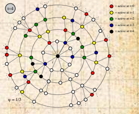

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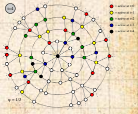

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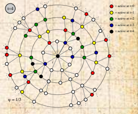

Expected size of spread

First connect θ_0 to θ_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).
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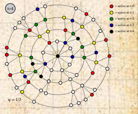

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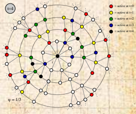


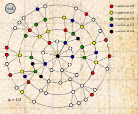
Expected size of spread

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

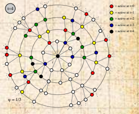


Expected size of spread

Iterative map for θ_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:

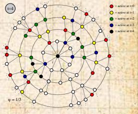
- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \to 0$.
- Depends on map $\theta_{t+1} = G(\theta_t; \phi_0)$.
- First: if self-starters are present, some activation is assured:

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

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

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



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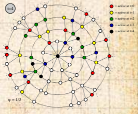

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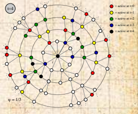

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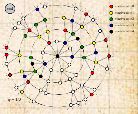


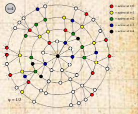
Expected size of spread:

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.

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.
- Tricky point: G depends on ϕ_0, so as we change ϕ_0, we also change G.
- A version of a critical mass model again.



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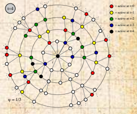

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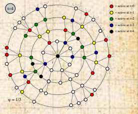

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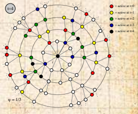

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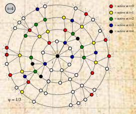

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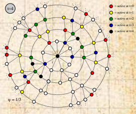
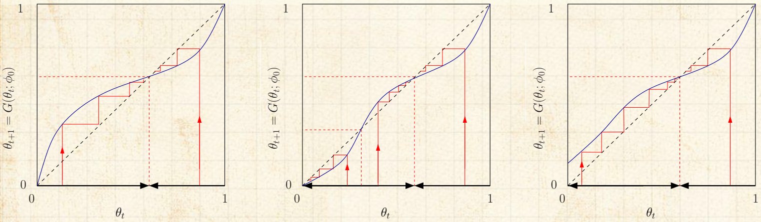
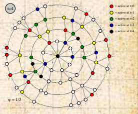


General fixed point story:



- Given $\theta_0 (= \phi_0)$, θ_∞ 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 ϕ_0.
- So choice of ϕ_0 dictates both G and starting point—can't start anywhere for a given G.



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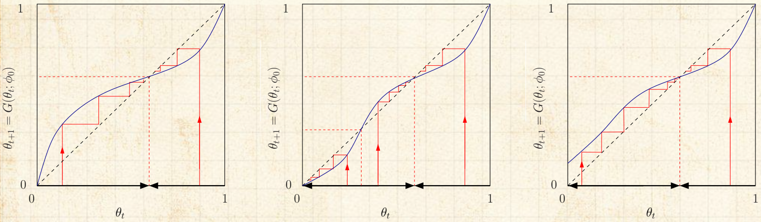

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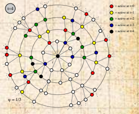

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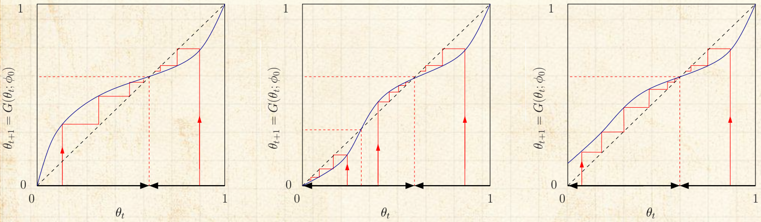

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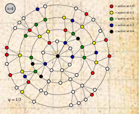

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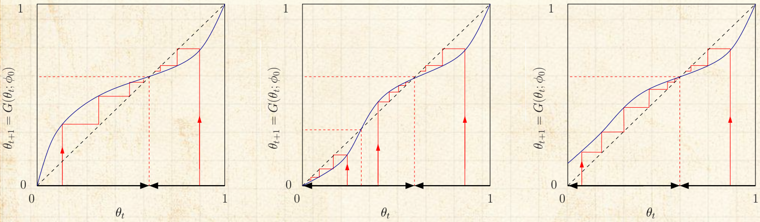

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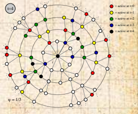
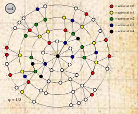
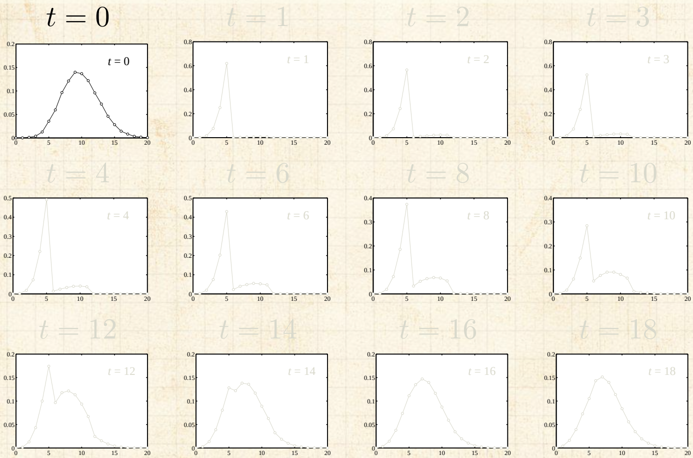


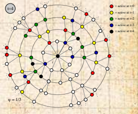
Outline



Early adopters—degree distributions



$P_{k,t}$ versus k



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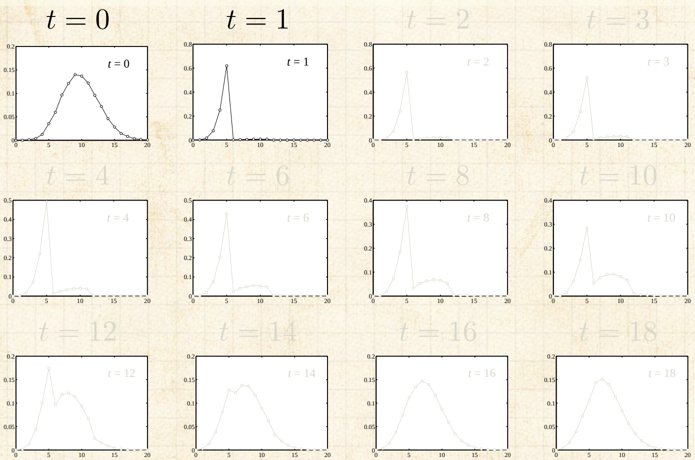

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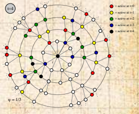

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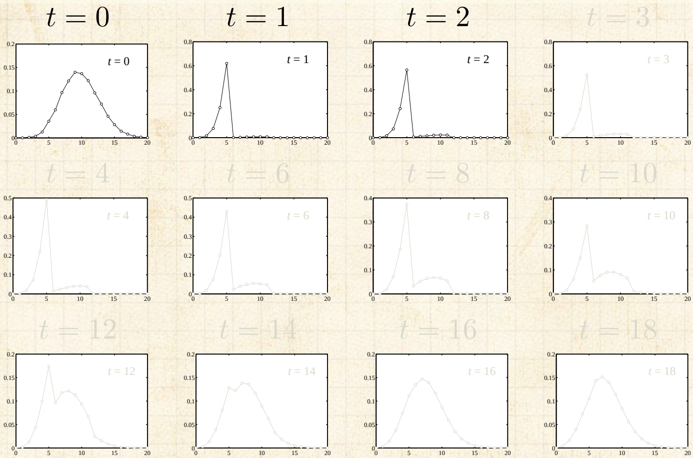

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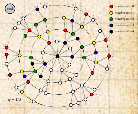

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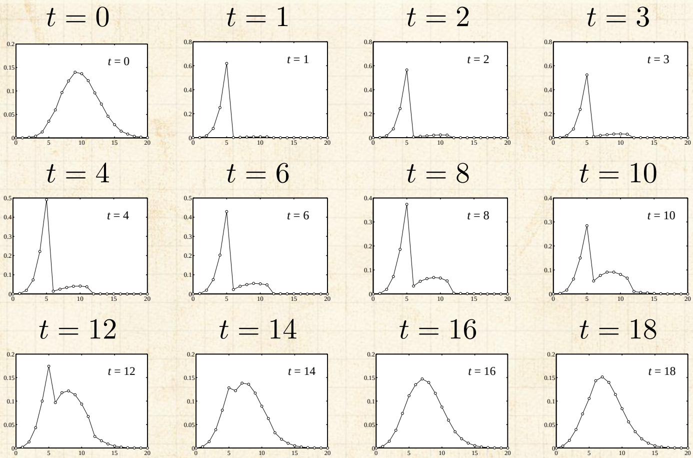

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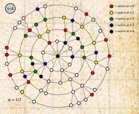
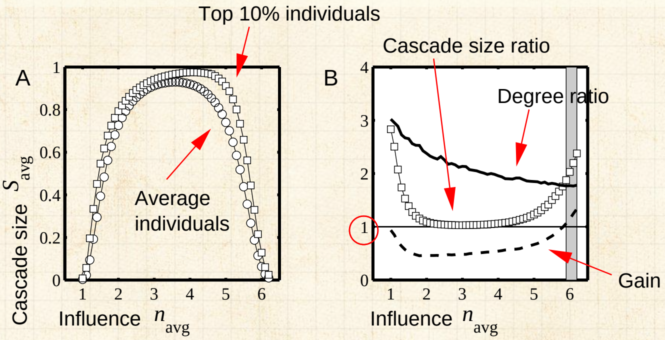
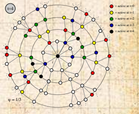


The multiplier effect:



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



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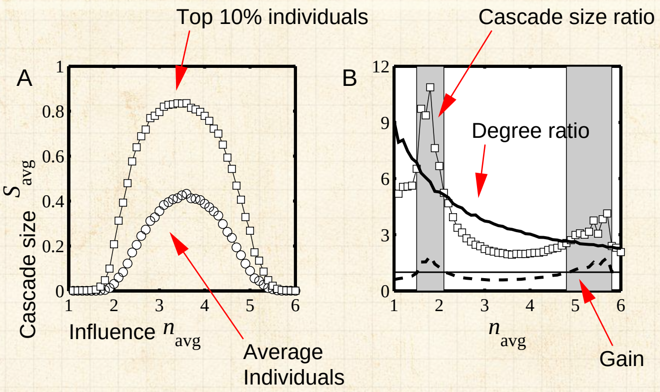
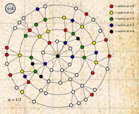
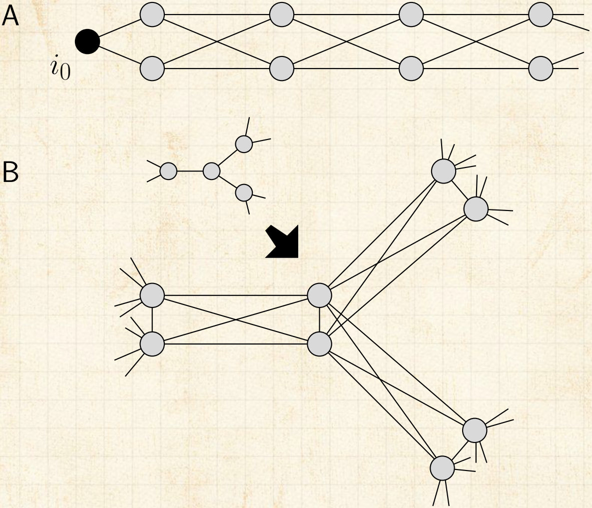


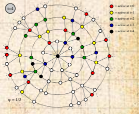
- Skewed influence distribution example.



Special subnetworks can act as triggers



$\phi = 1/3$ for all nodes



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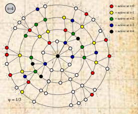
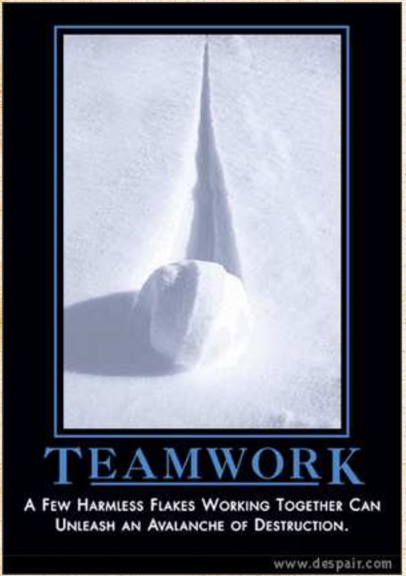
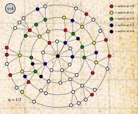


The power of groups...

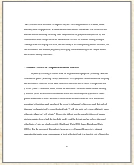


despair.com

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

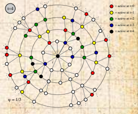


Extensions



"Threshold Models of Social Influence"
Watts and Dodds,
The Oxford Handbook of Analytical Sociology, , 475–497, 2009. [28]

- 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



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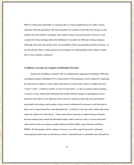

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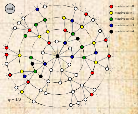

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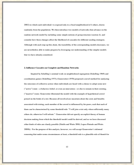

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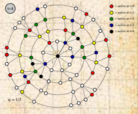

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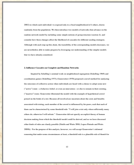

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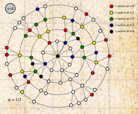
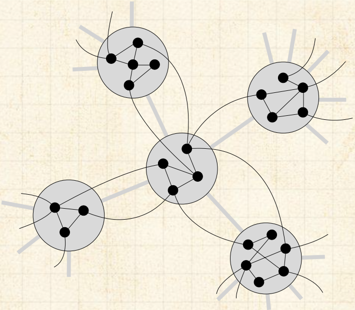
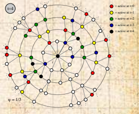


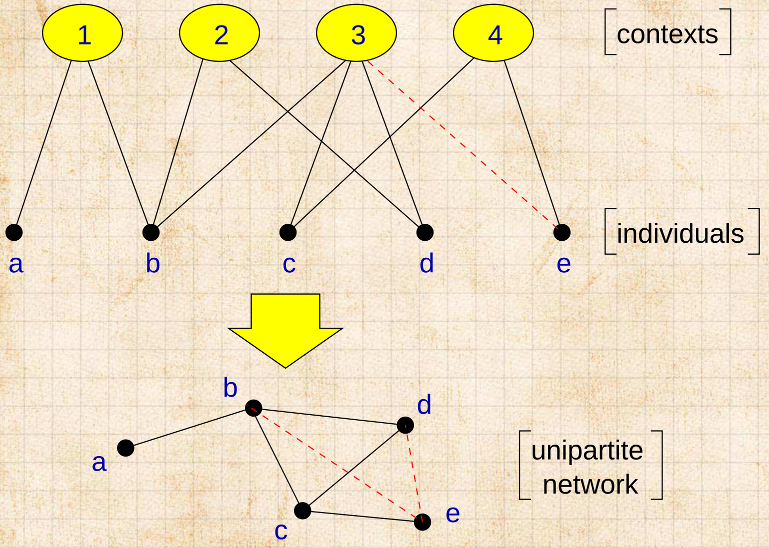
Group structure—Ramified random networks

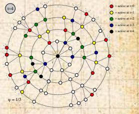


p = intergroup connection probability
q = intragroup connection probability.

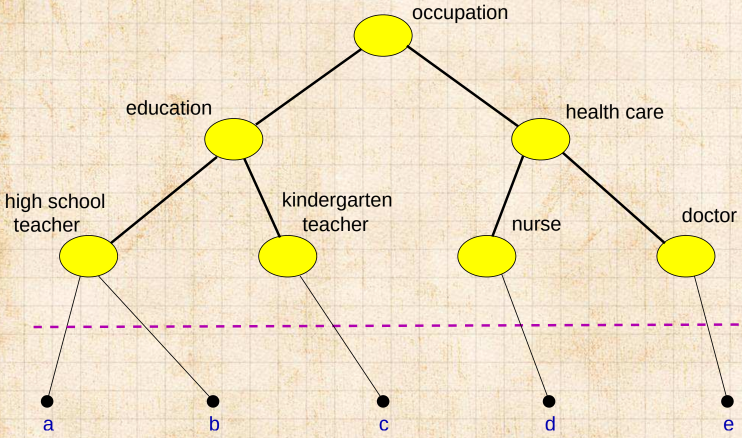


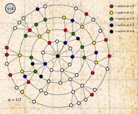
Bipartite networks



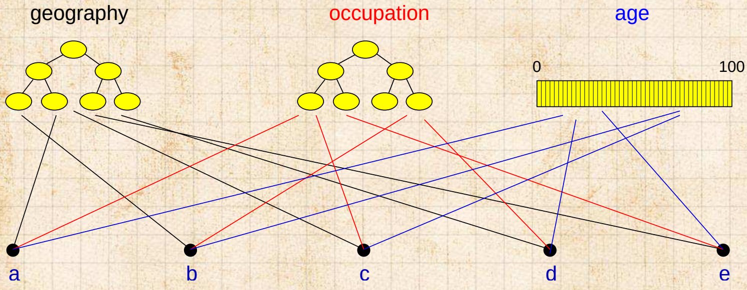


Context distance

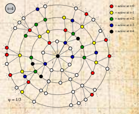




Generalized affiliation model

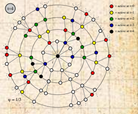


(Blau & Schwartz, Simmel, Breiger)



Generalized affiliation model networks with triadic closure

- Connect nodes with probability $\propto \exp^{-\alpha d}$ where
  α = homophily parameter
  and
  d = distance between nodes (height of lowest common ancestor)
- τ_1 = intergroup probability of friend-of-friend connection
- τ_2 = intragroup probability of friend-of-friend connection



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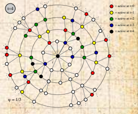

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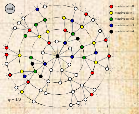
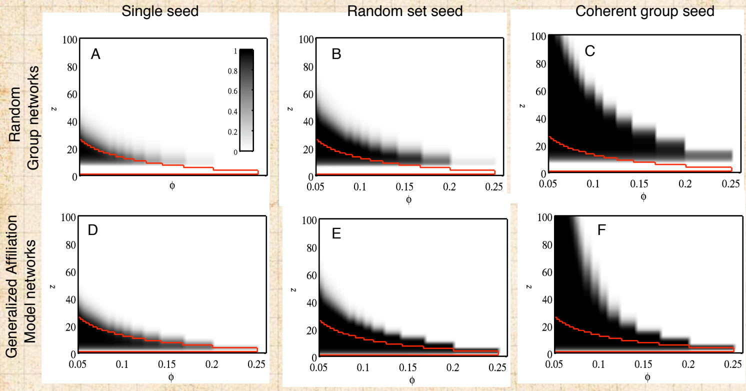
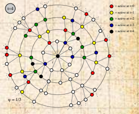
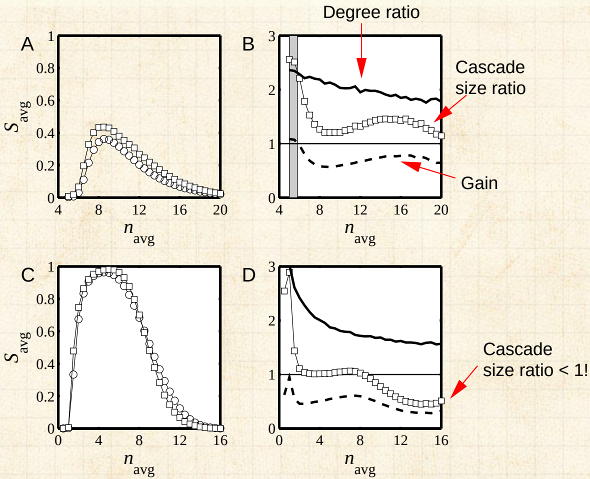


Cascade windows for group-based networks

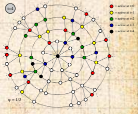




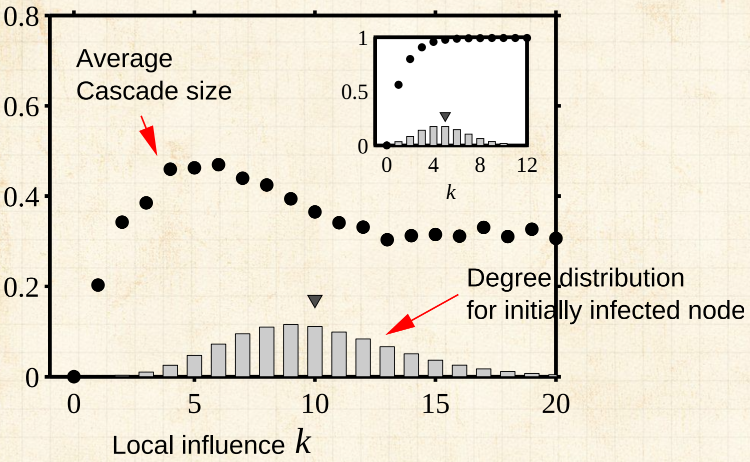
Multiplier effect for group-based networks:



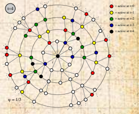
- Multiplier almost always below 1.



Assortativity in group-based networks



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



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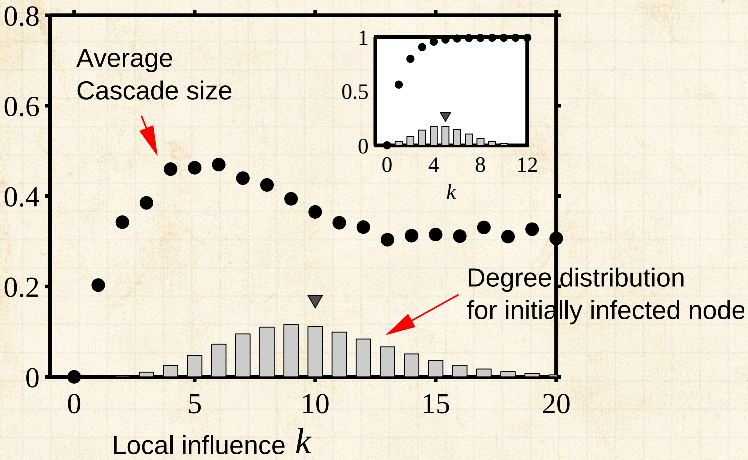

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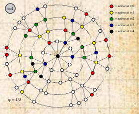
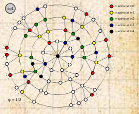


Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.



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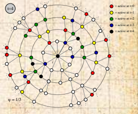

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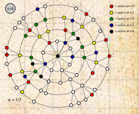

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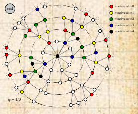

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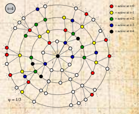

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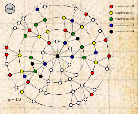

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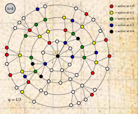

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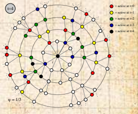
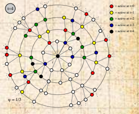


Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (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.



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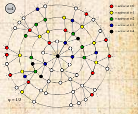

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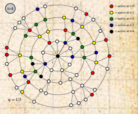

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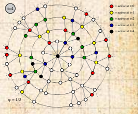

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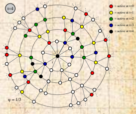

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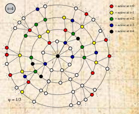
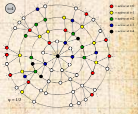


Spreading and unspreading: Empires

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

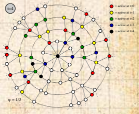


References I

[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

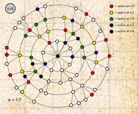


References II

[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

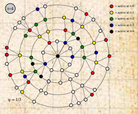


References III

[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

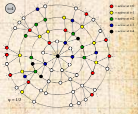


References IV

[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.

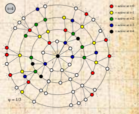


References V

[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

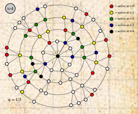


References VI

[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



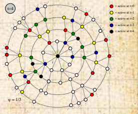
References VII

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

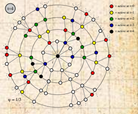


References VIII

[23] 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

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

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

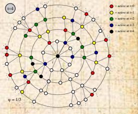


References IX

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

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

[28] 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



References X

[29] U. Wilensky.
Netlogo segregation model.
http://ccl.northwestern.edu/netlogo/models/Segregation.
Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL., 1998.