Social Contagion

Principles of Complex Systems | @pocsvox
CSYS/MATH 300, Fall, 2016 | #FallPoCS2016

Prof. Peter Dodds | @peterdodds

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

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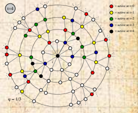
What's the Story?



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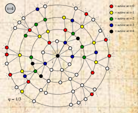
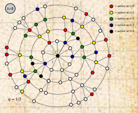
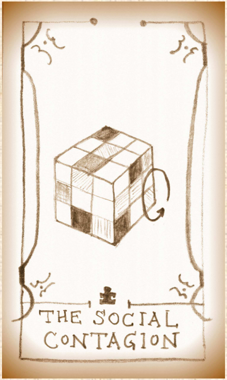


Outline




THE SUN
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 DATA POOR
THE POURING DATA
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE ARK OF THE RANDOM NETWORK
THE STRANGENESS OF FRIENDS
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
THE UNENDING PANDEMICS
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING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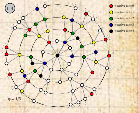

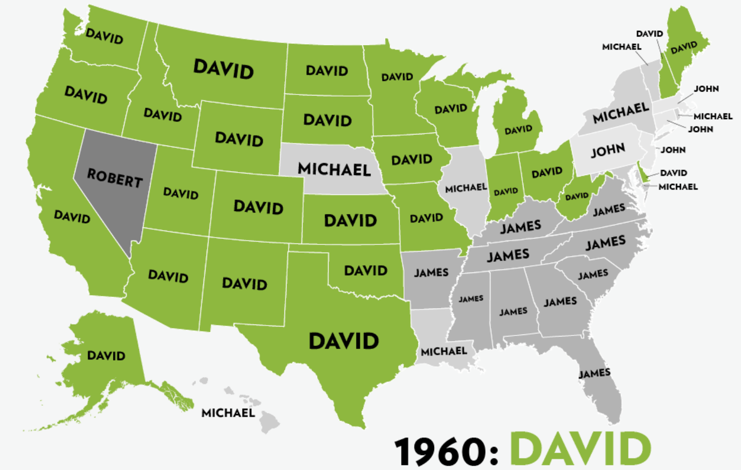

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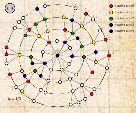

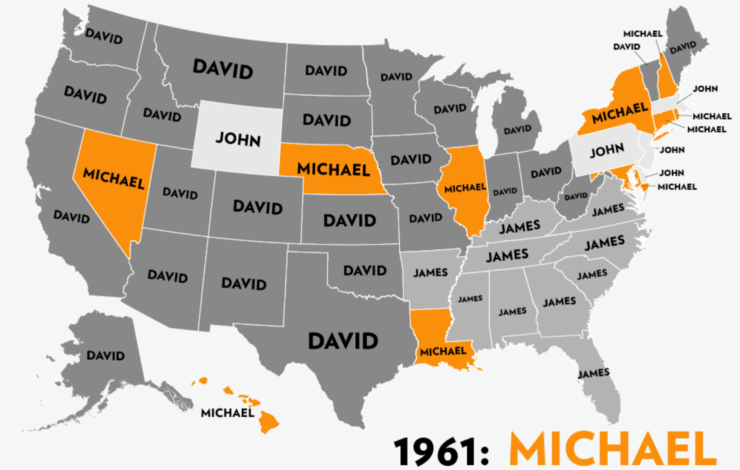

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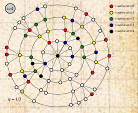

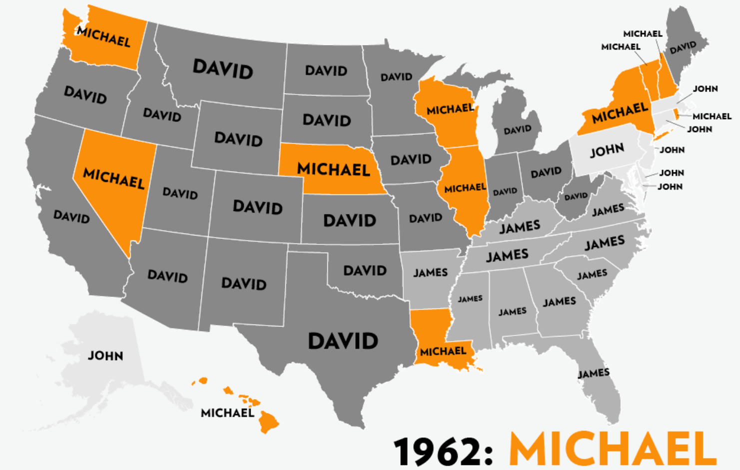

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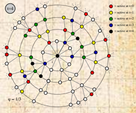

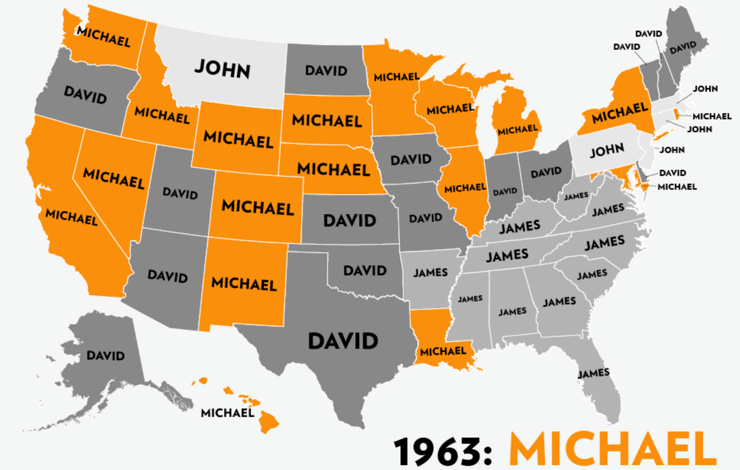

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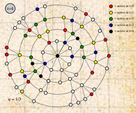

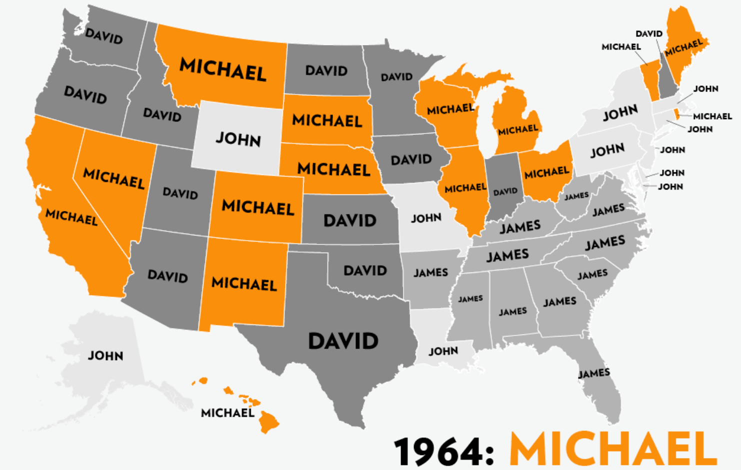

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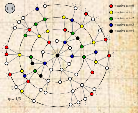

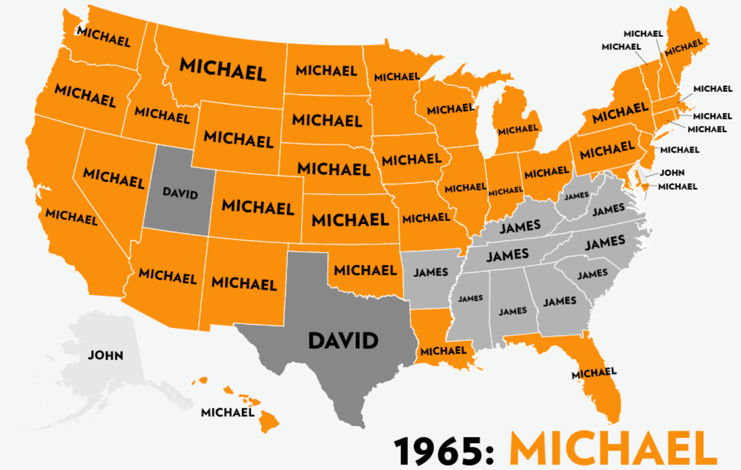

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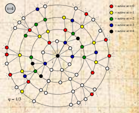

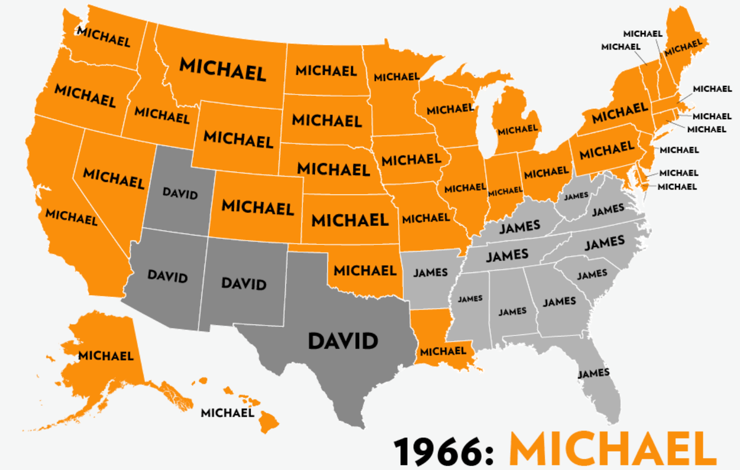

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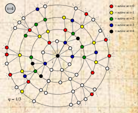

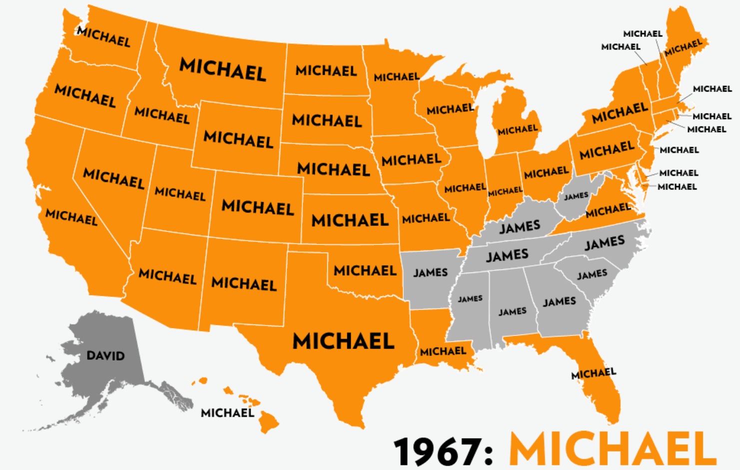

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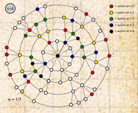

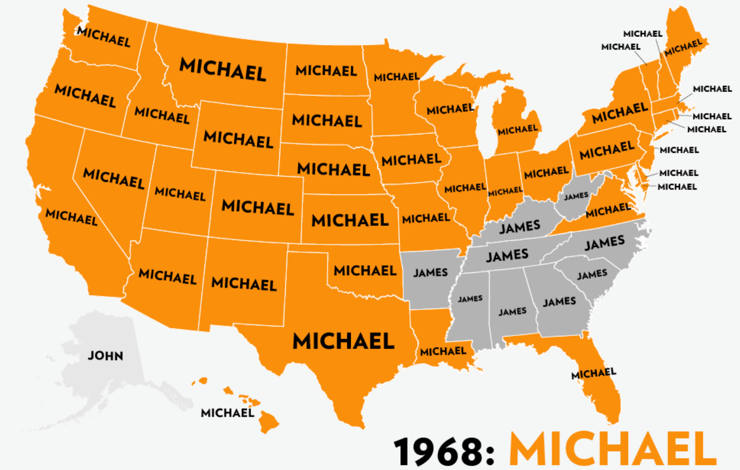

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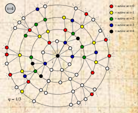

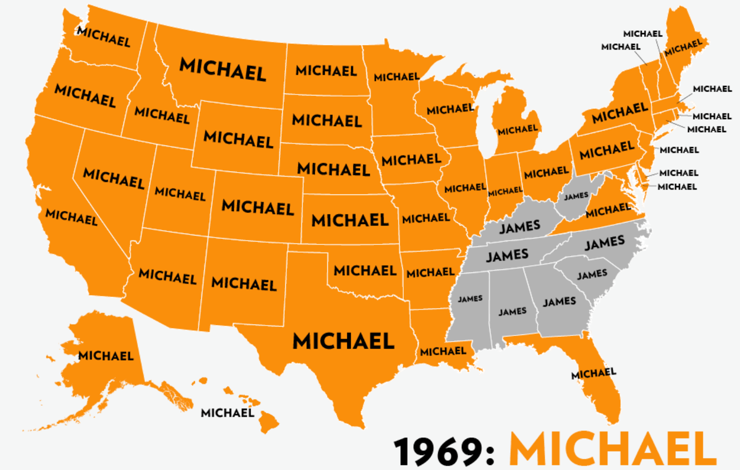

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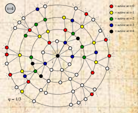

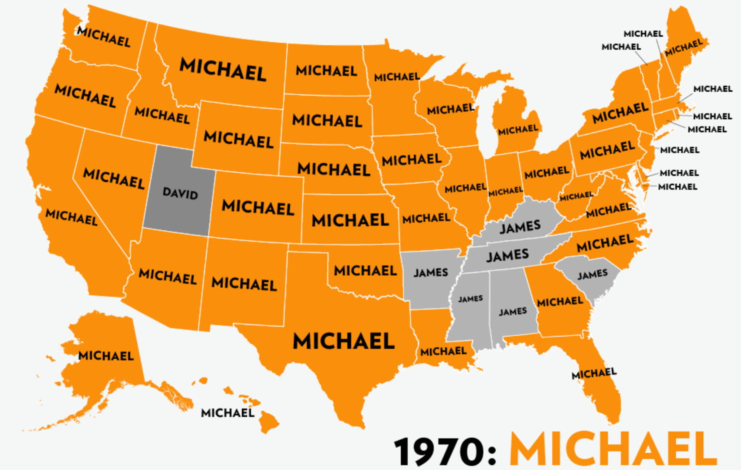

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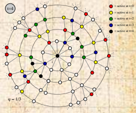

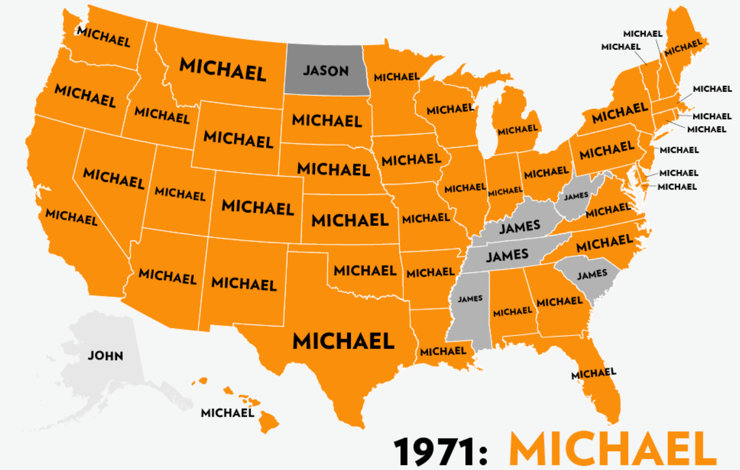

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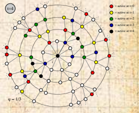

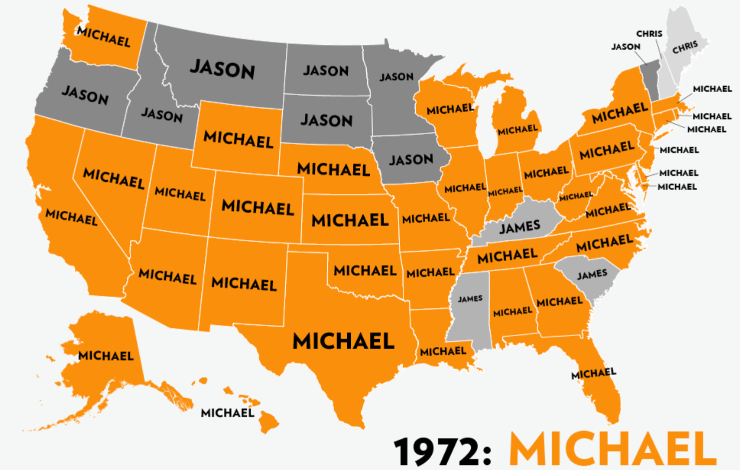

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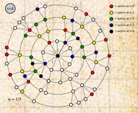

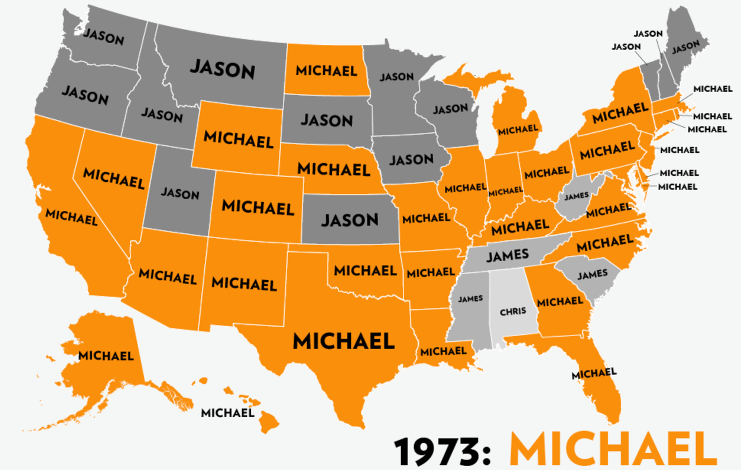

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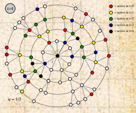

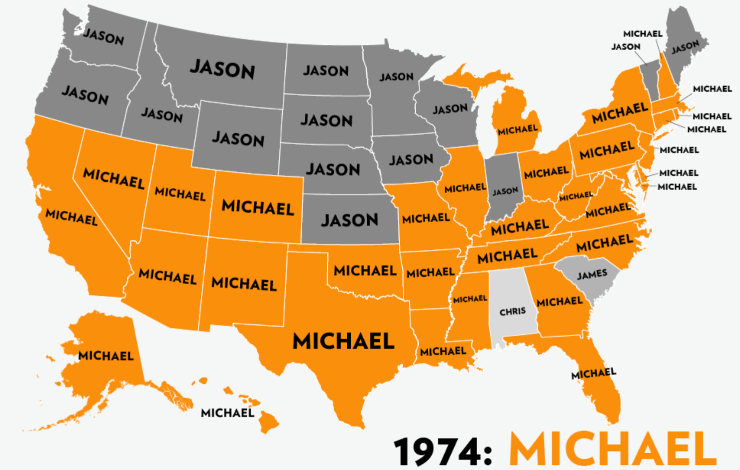

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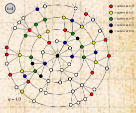

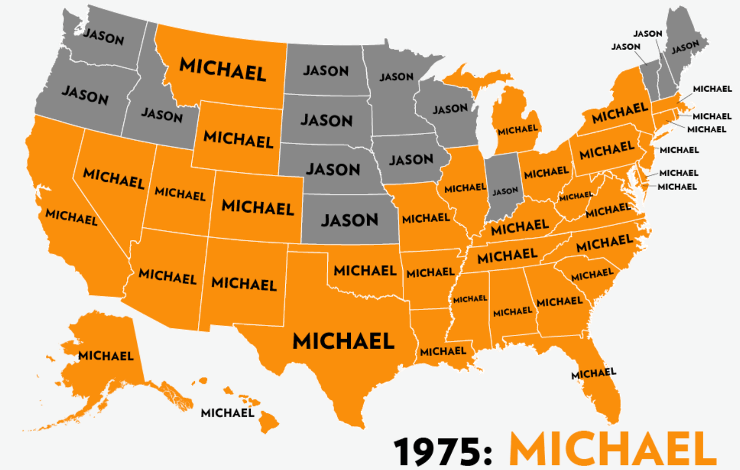

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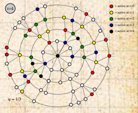

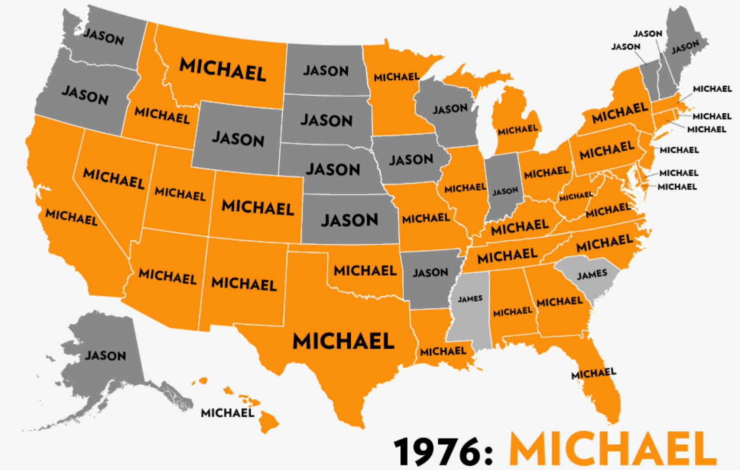

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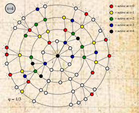

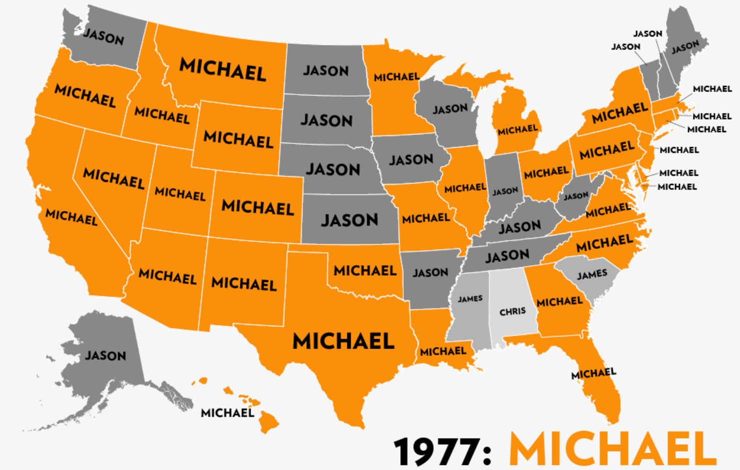

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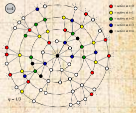

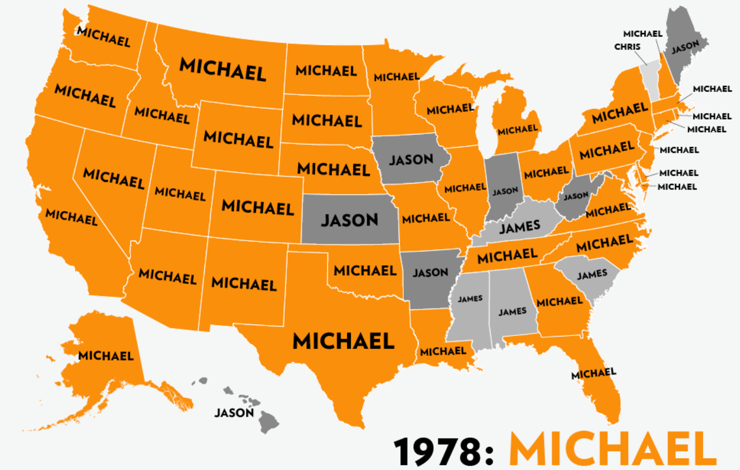

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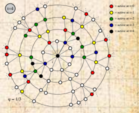

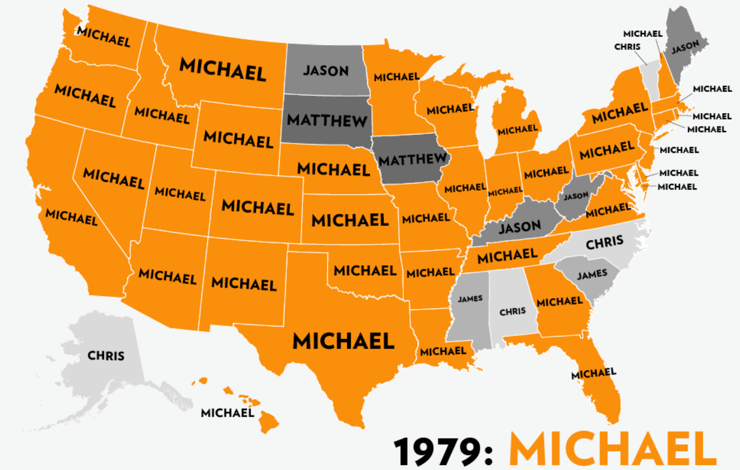

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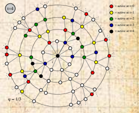

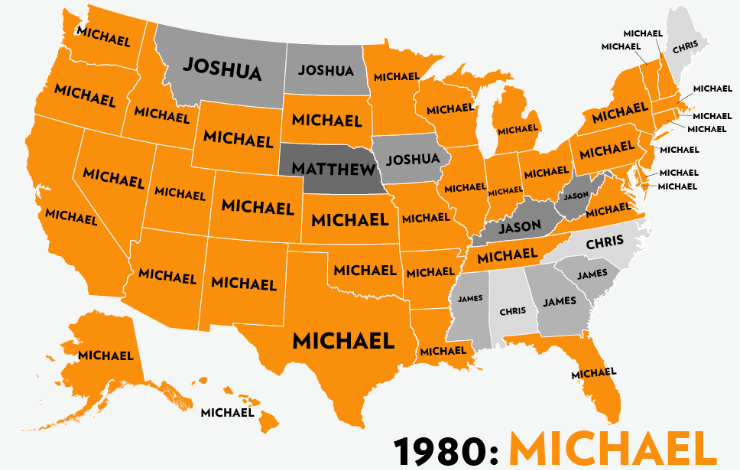

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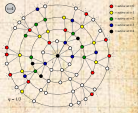

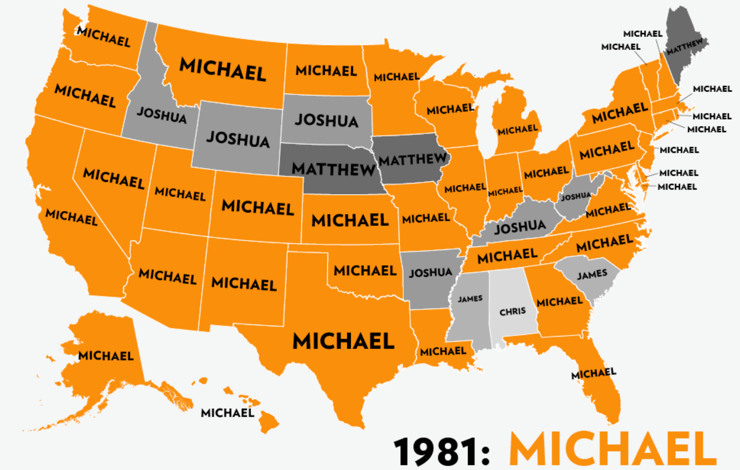

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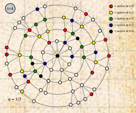

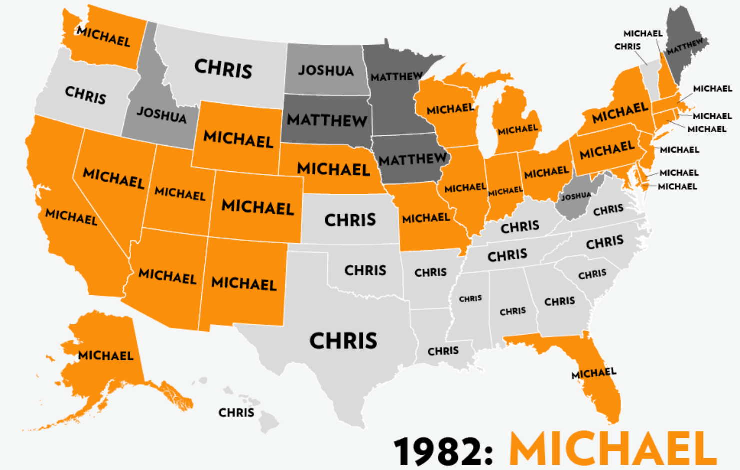

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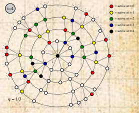

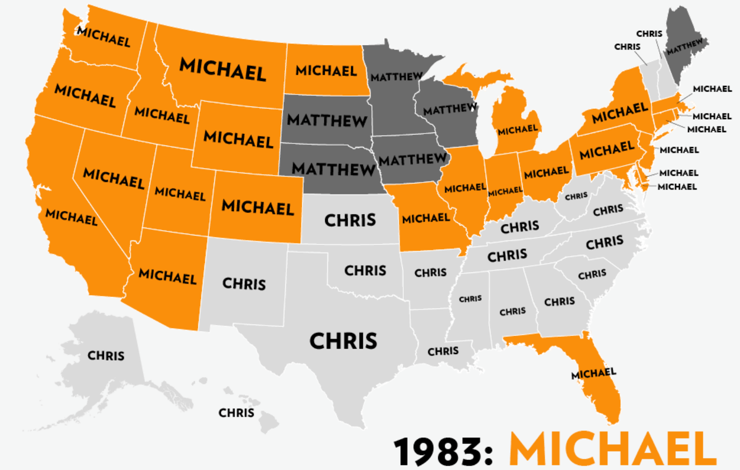

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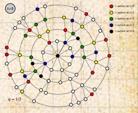

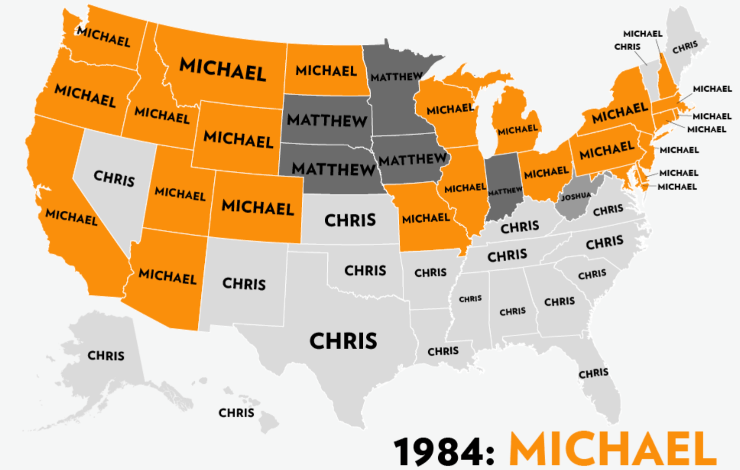

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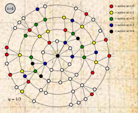

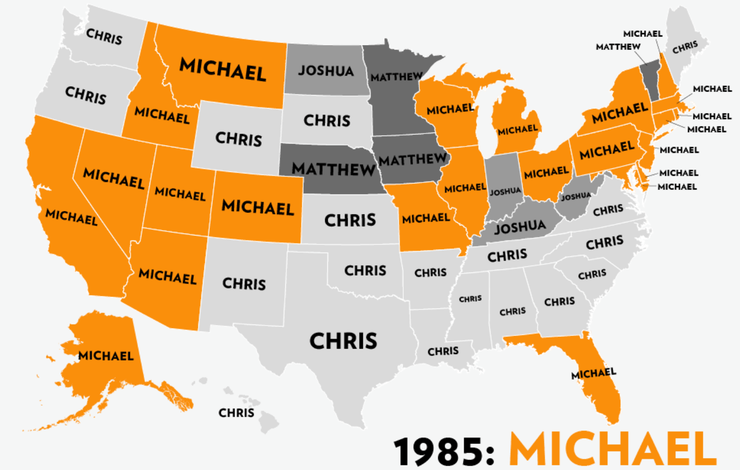

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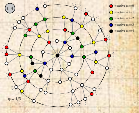

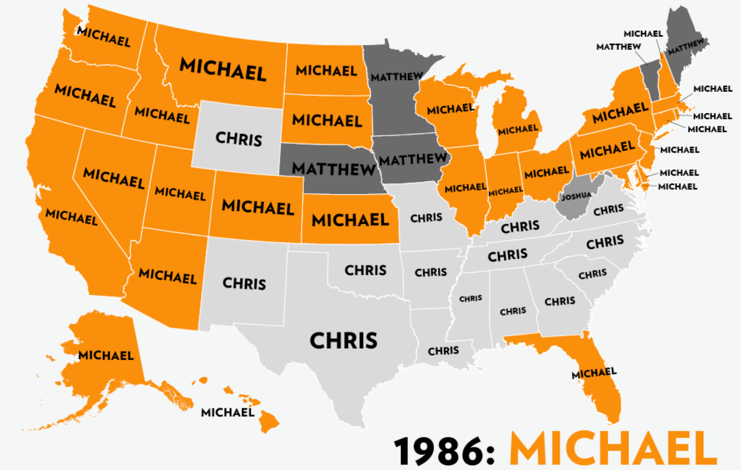

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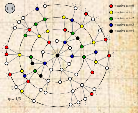

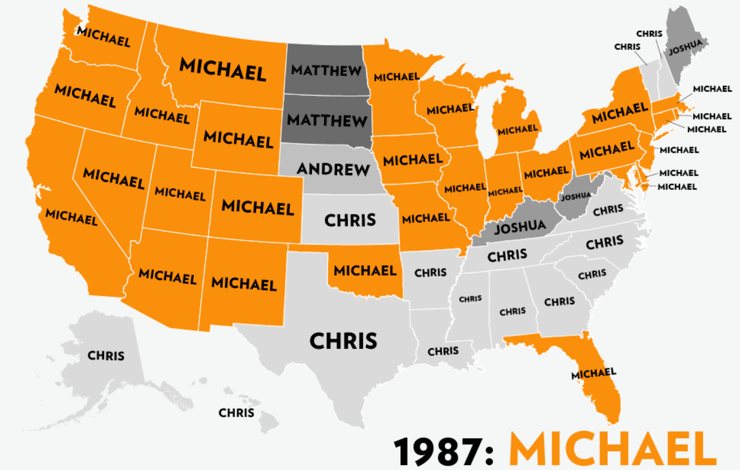

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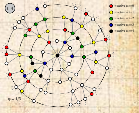

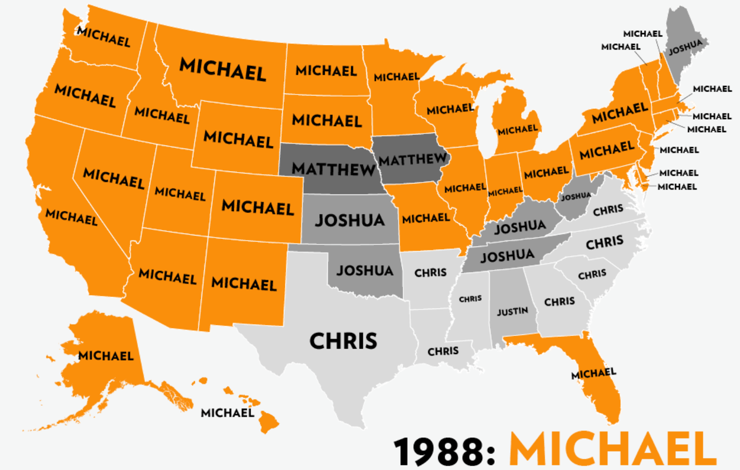

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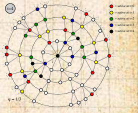

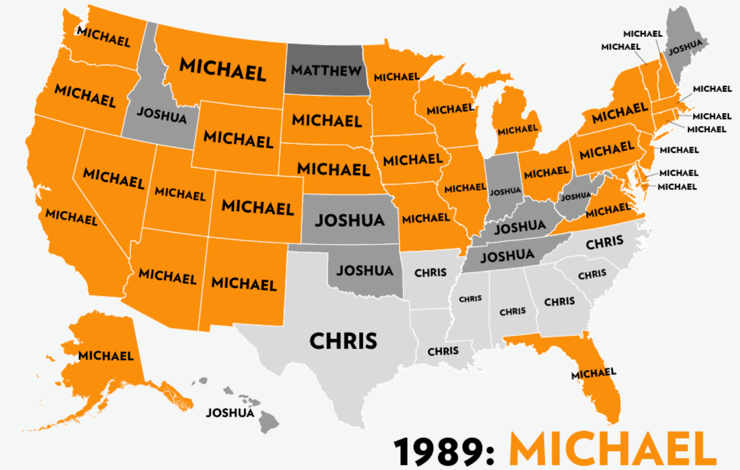

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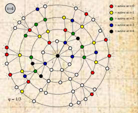

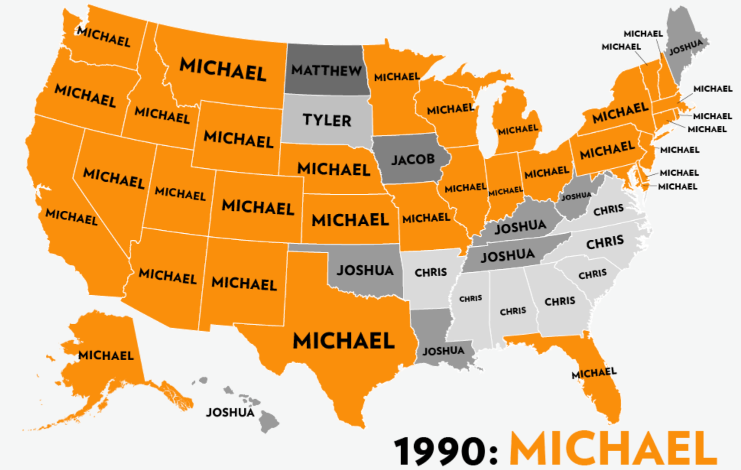

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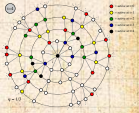

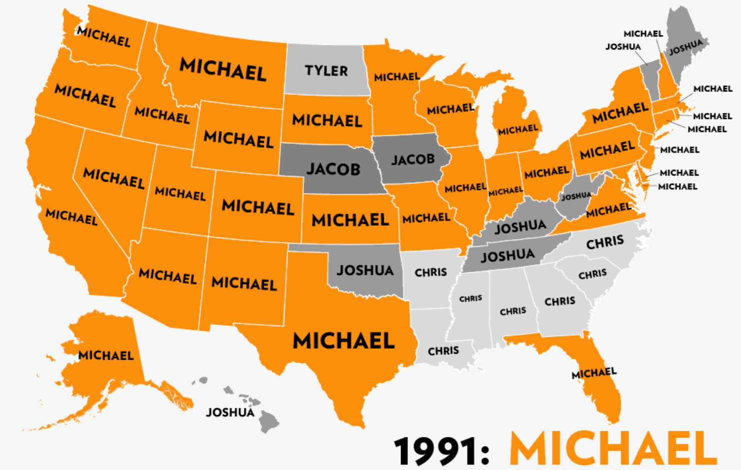

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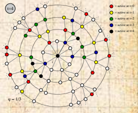

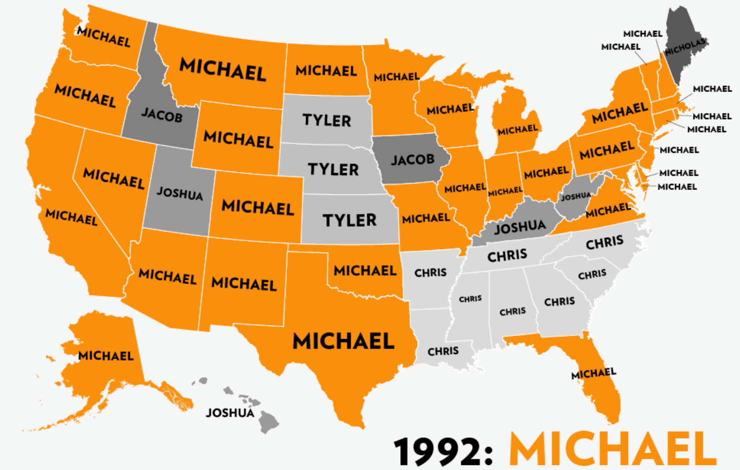

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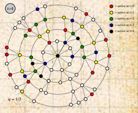

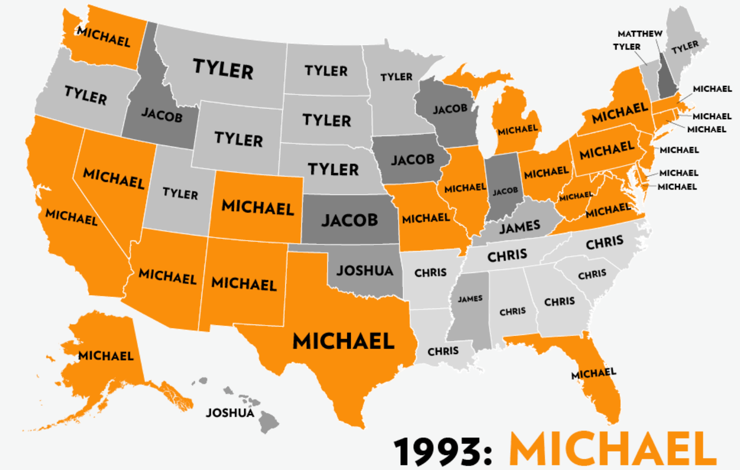

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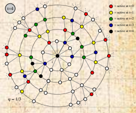

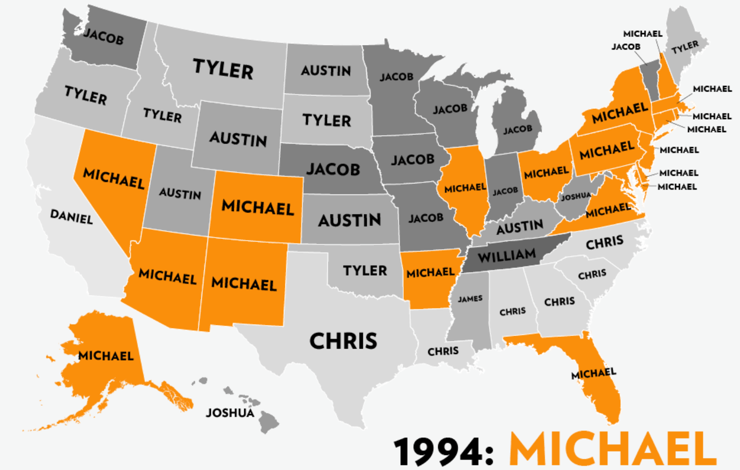

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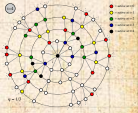

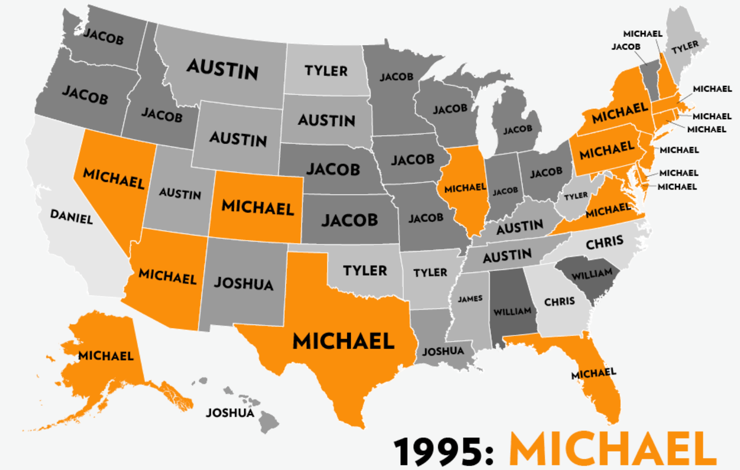

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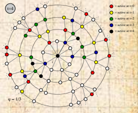

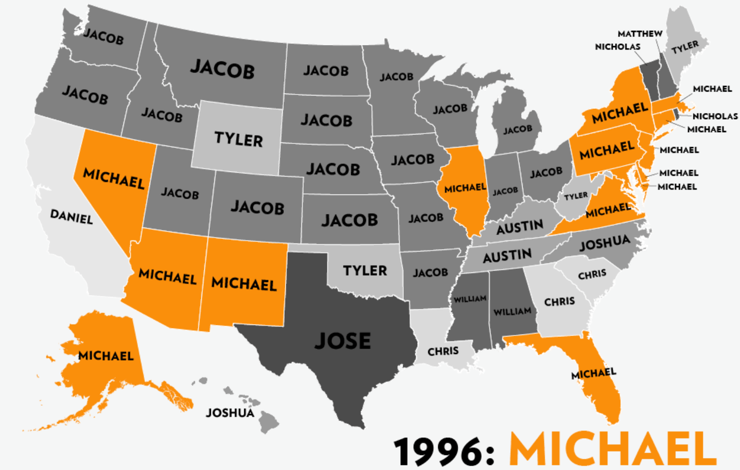

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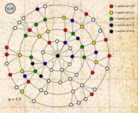

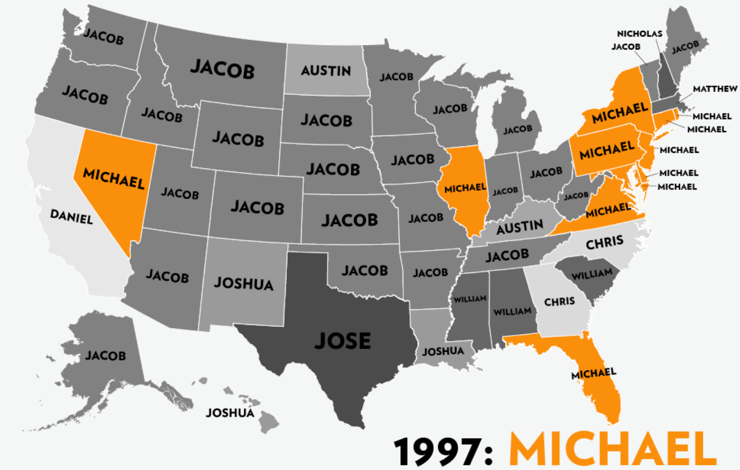

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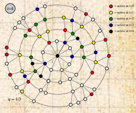

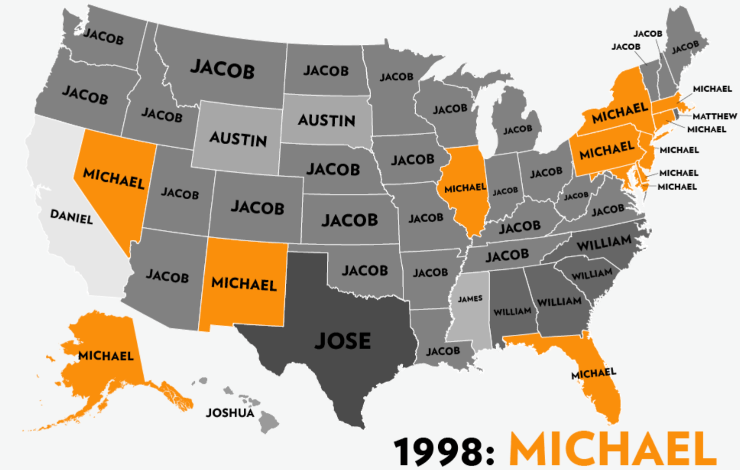

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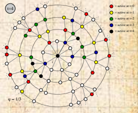

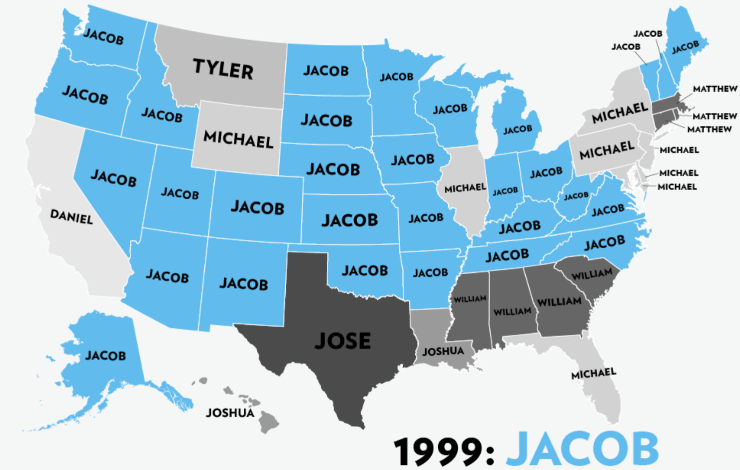

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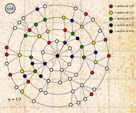

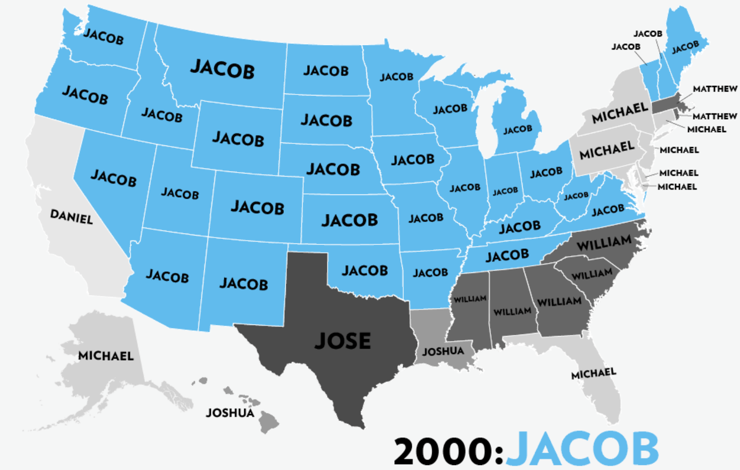

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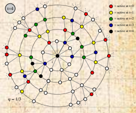

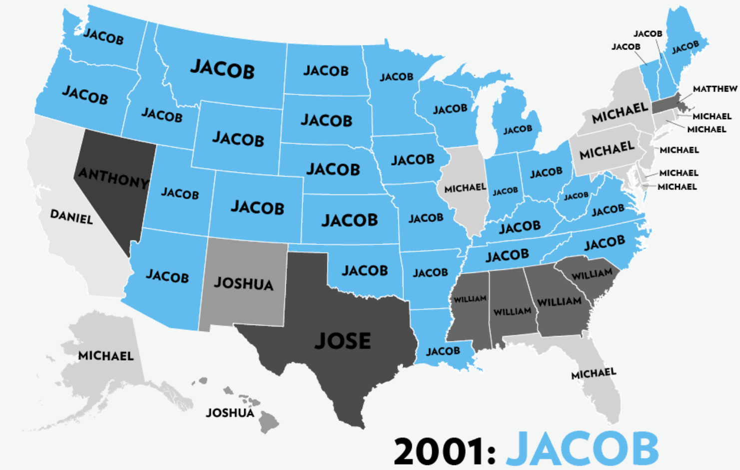

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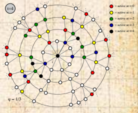

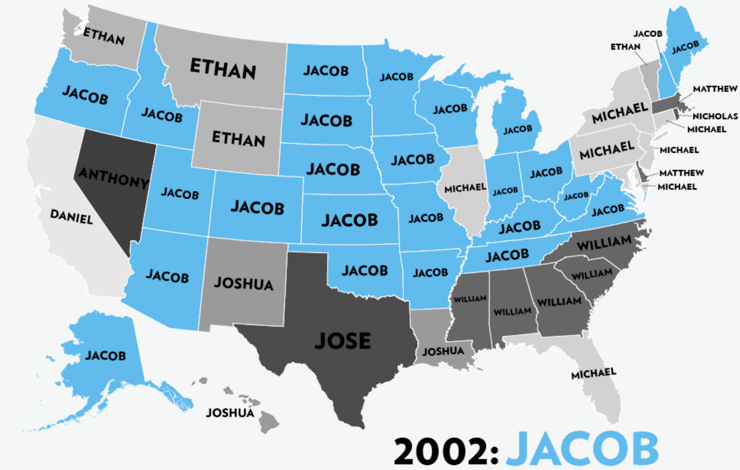

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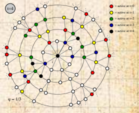

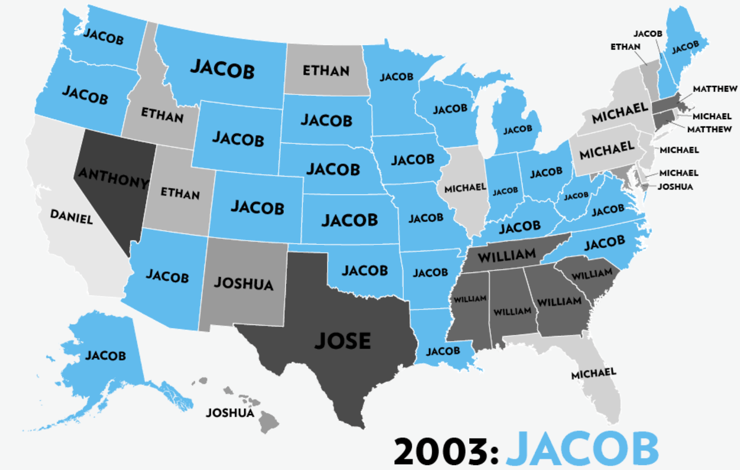

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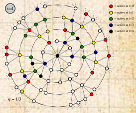

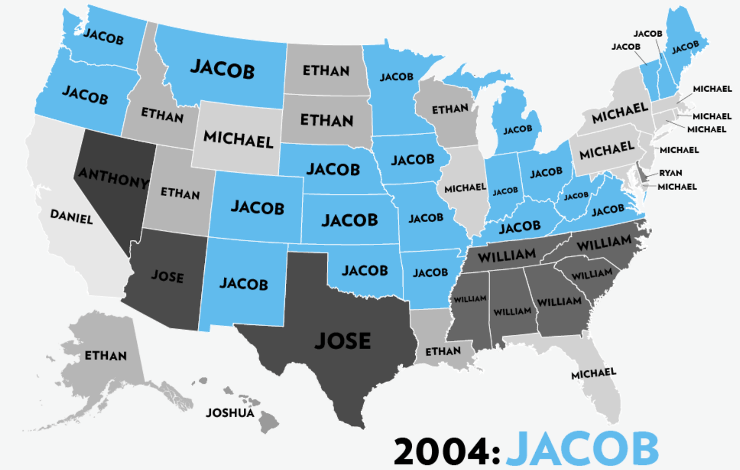

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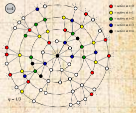

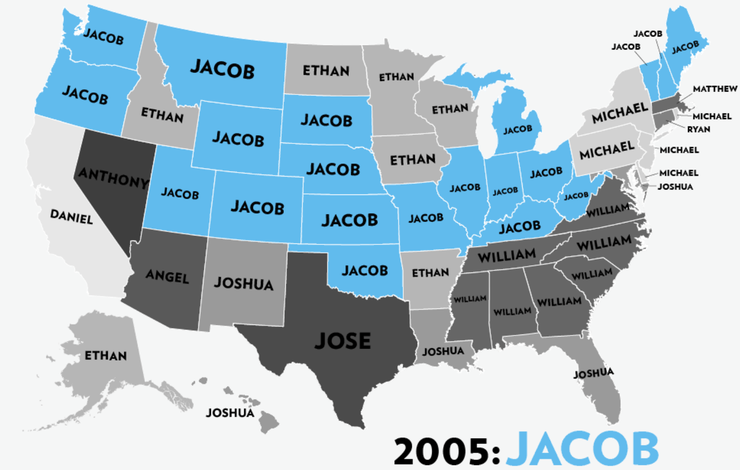

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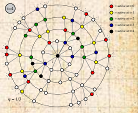

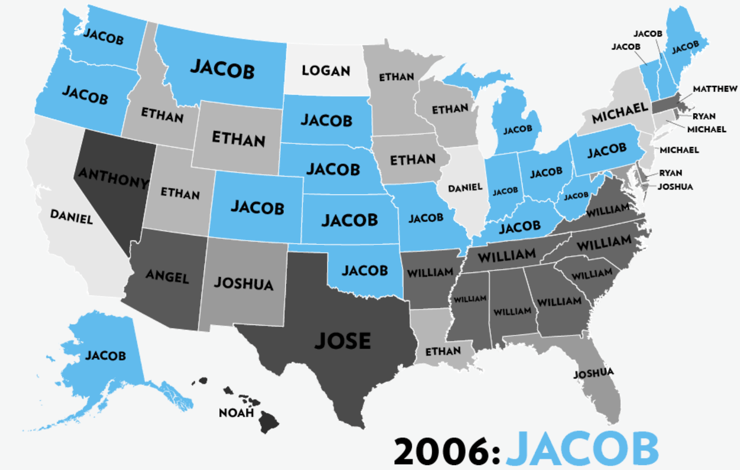

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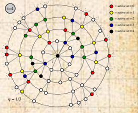

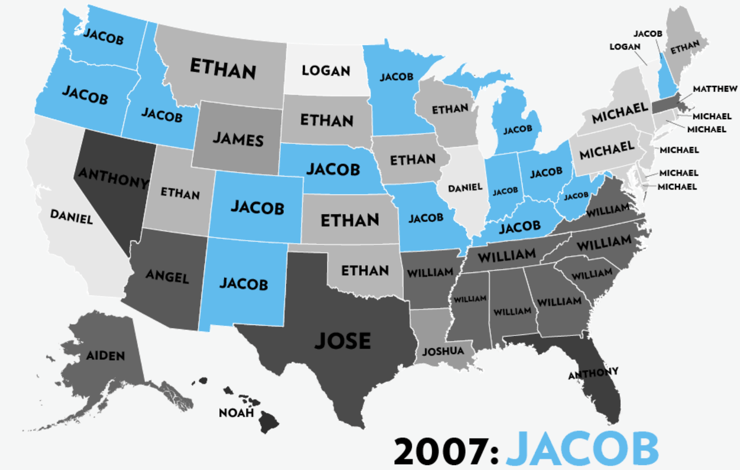

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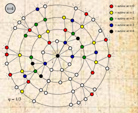

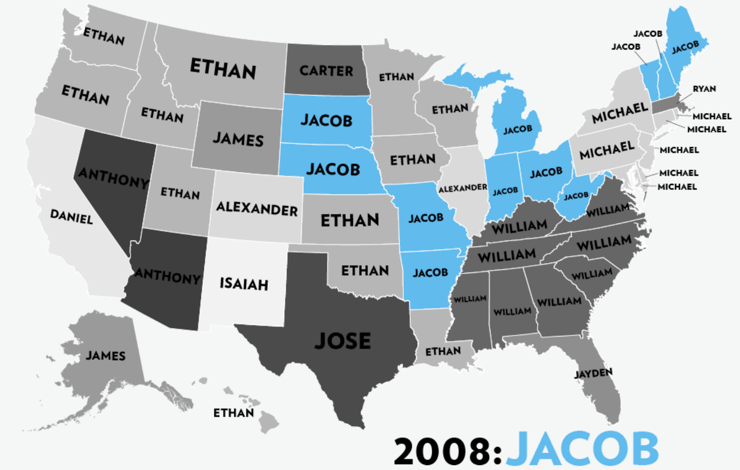

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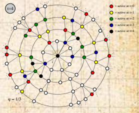

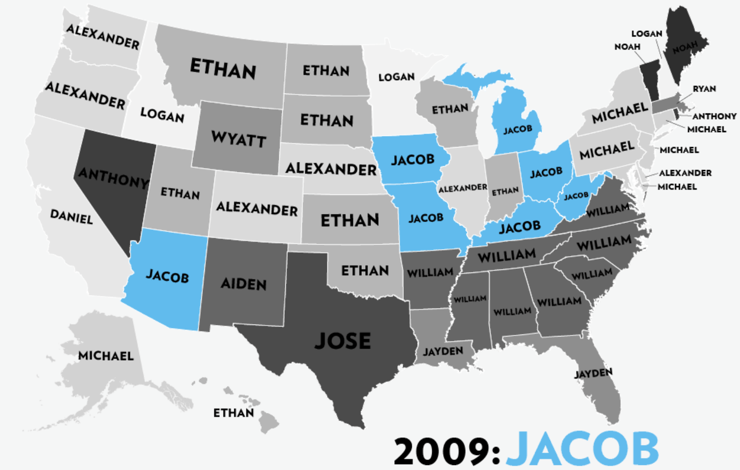

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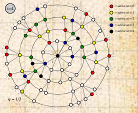

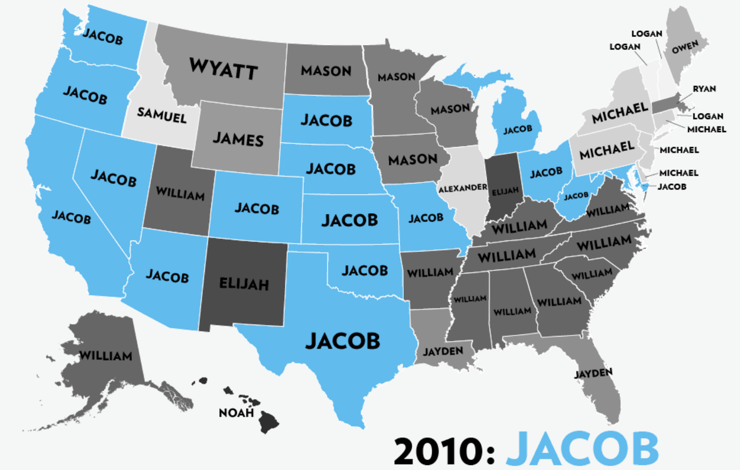

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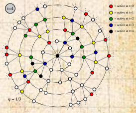

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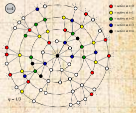

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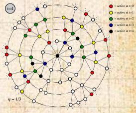

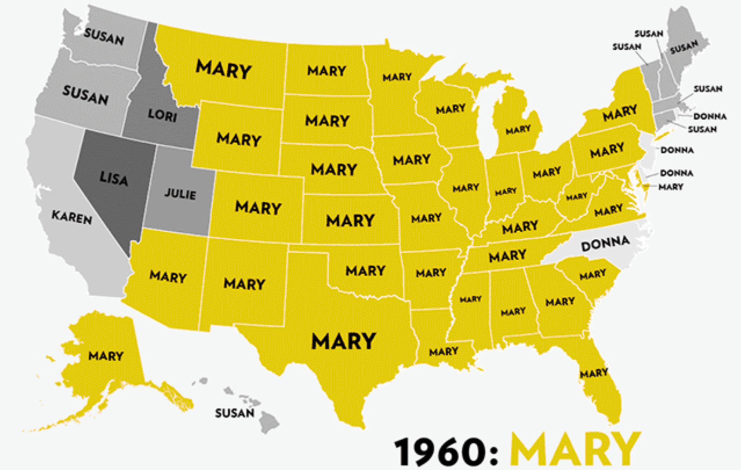

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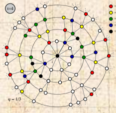

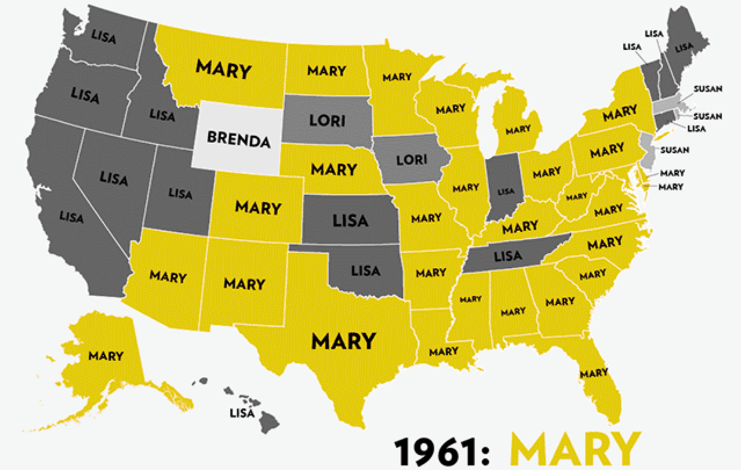

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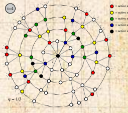

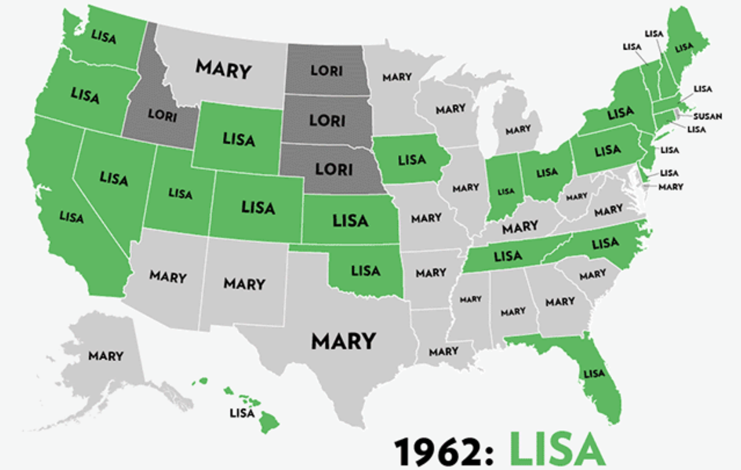

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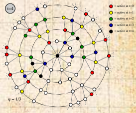

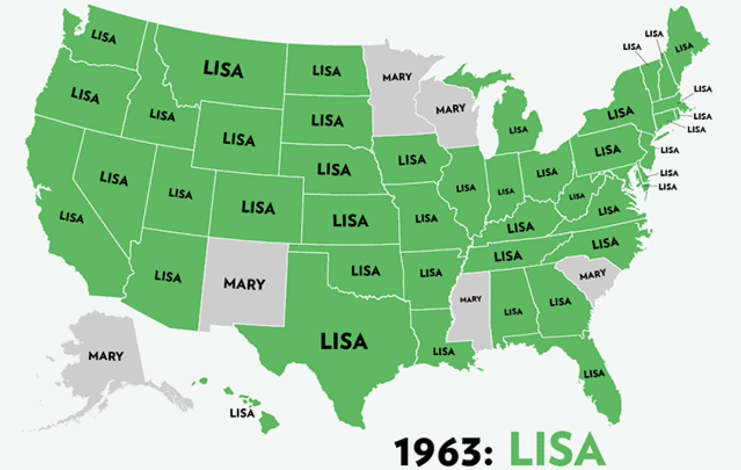

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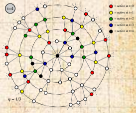

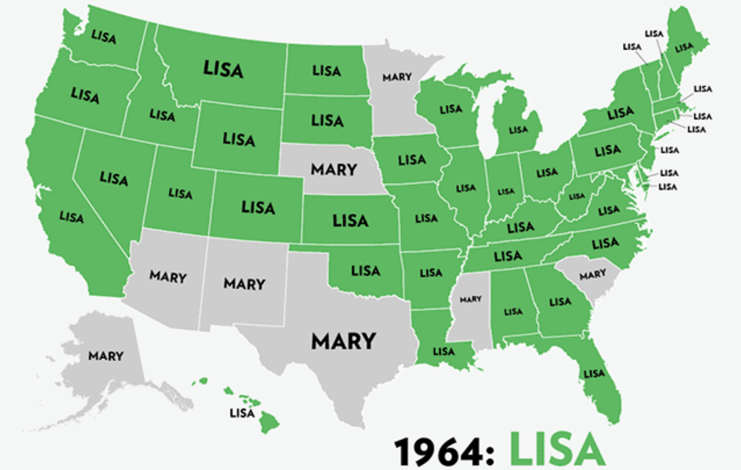

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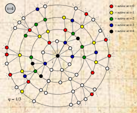

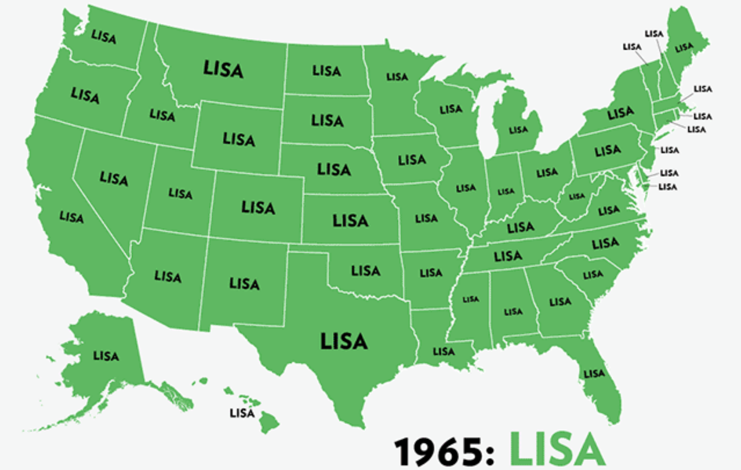

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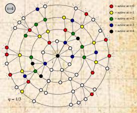

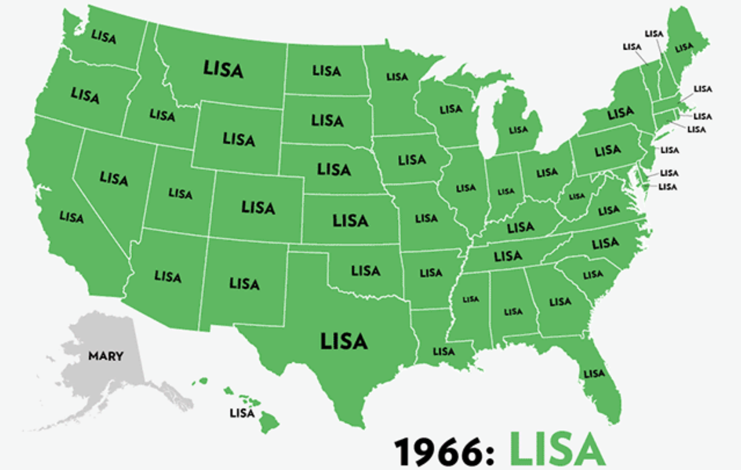

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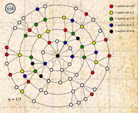

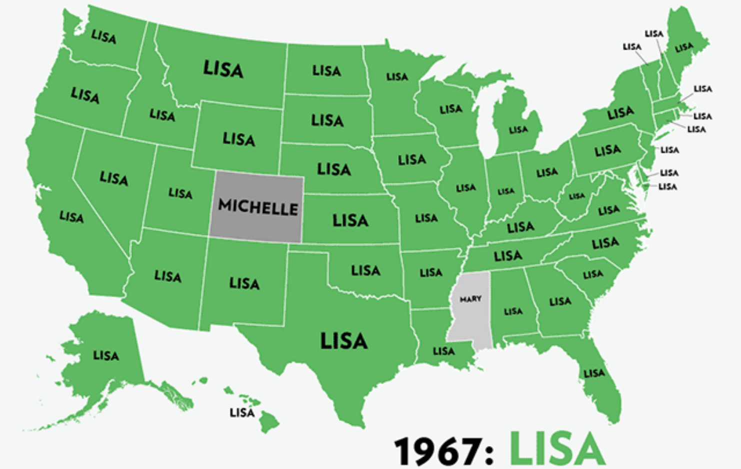

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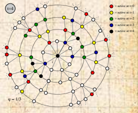

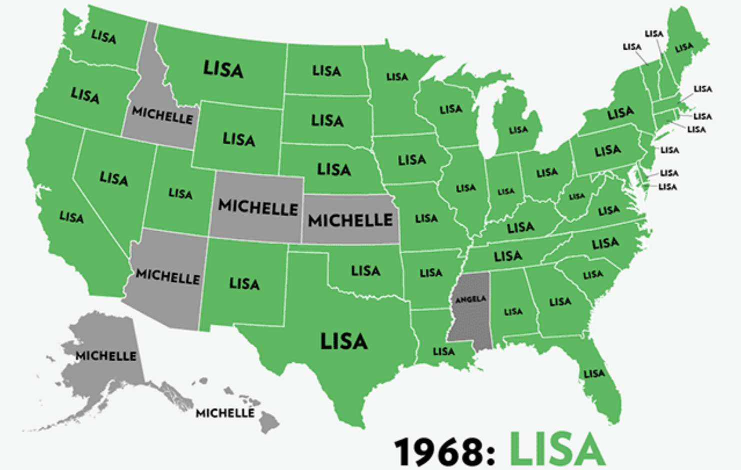

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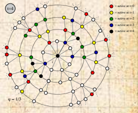

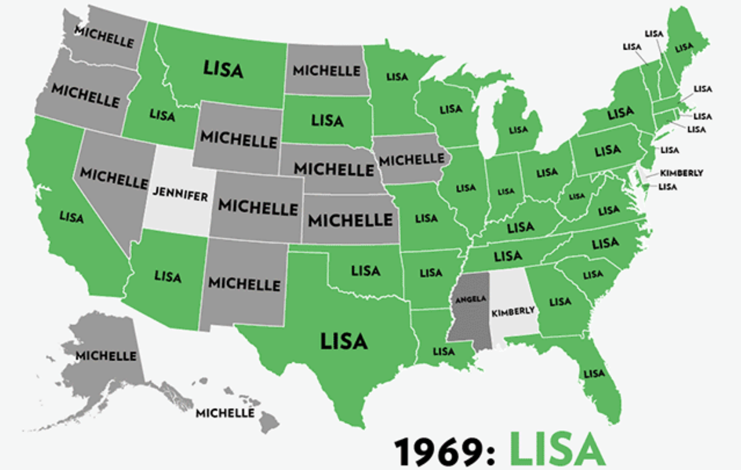

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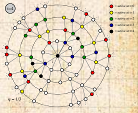

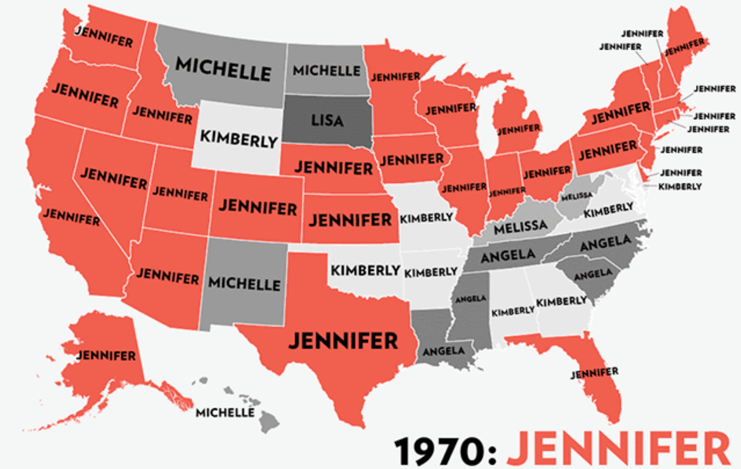

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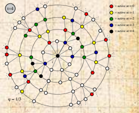

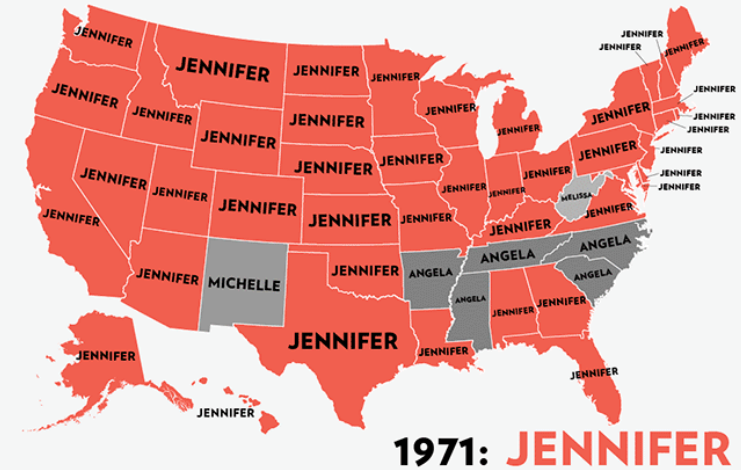

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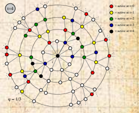

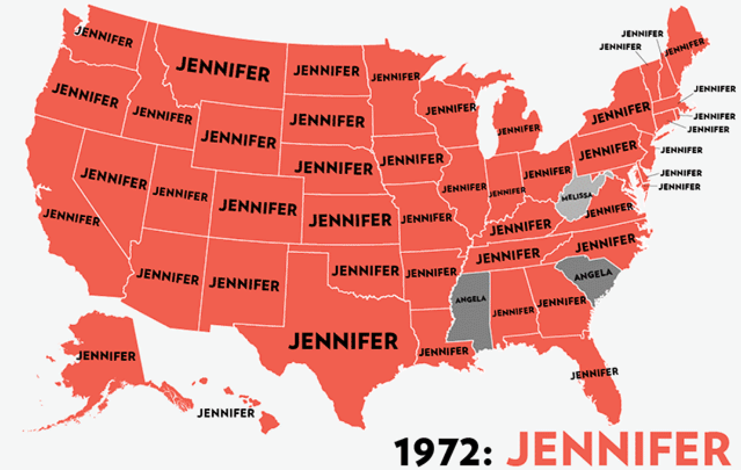

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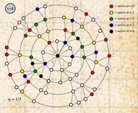

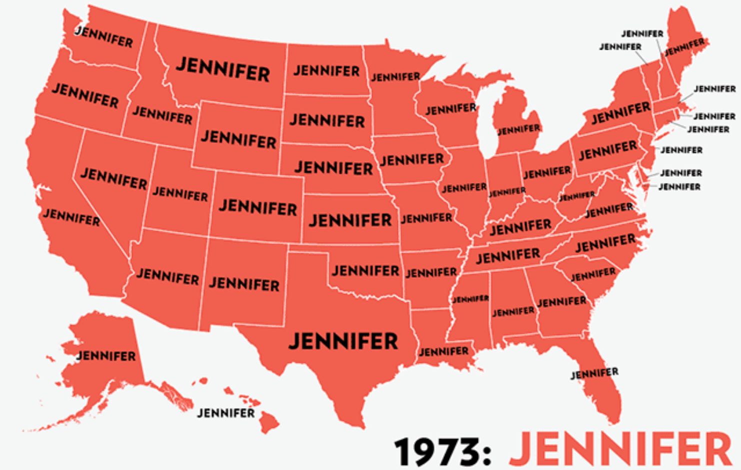

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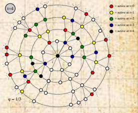

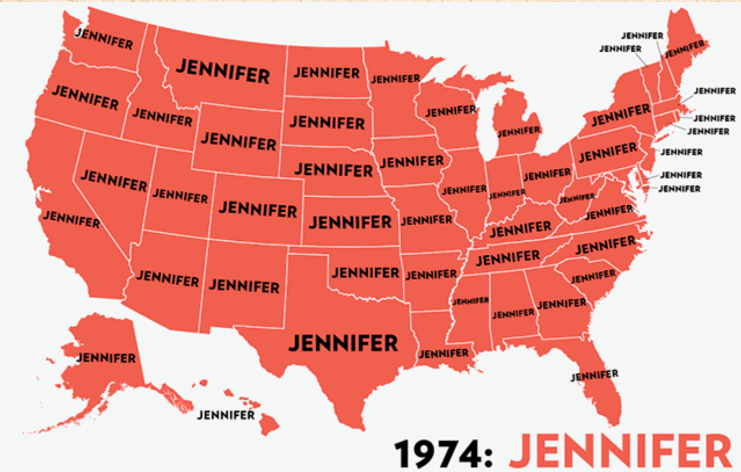

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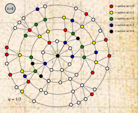

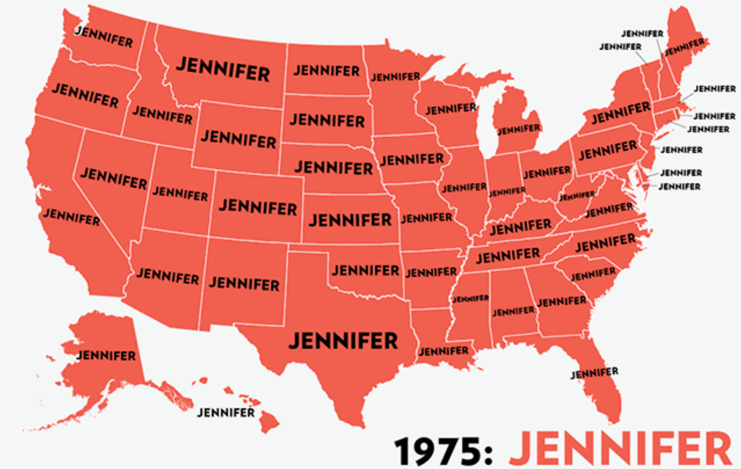

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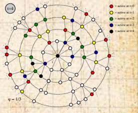

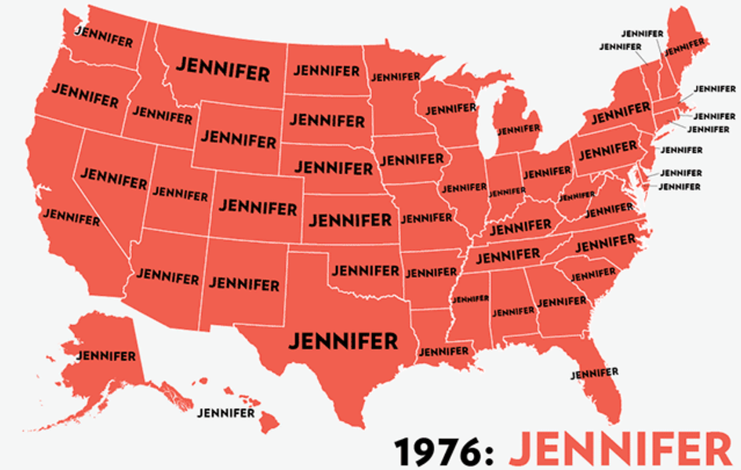

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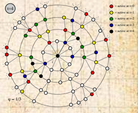

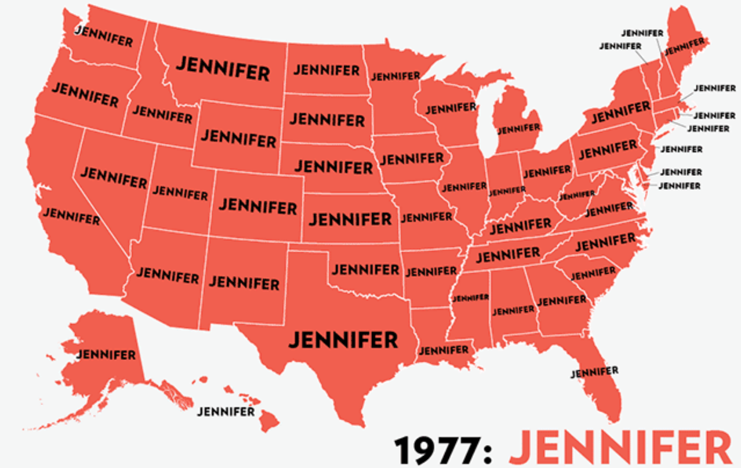

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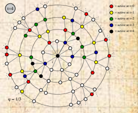

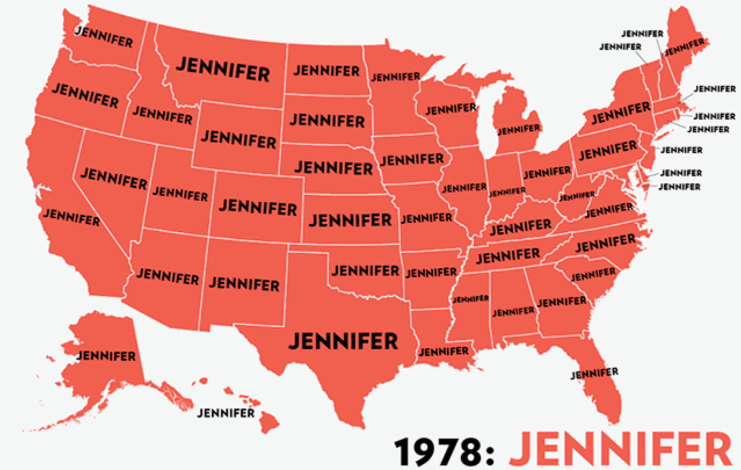

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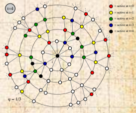

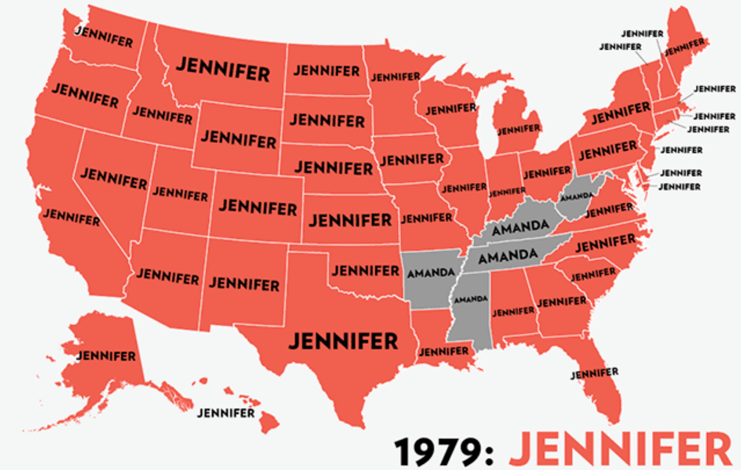

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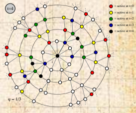

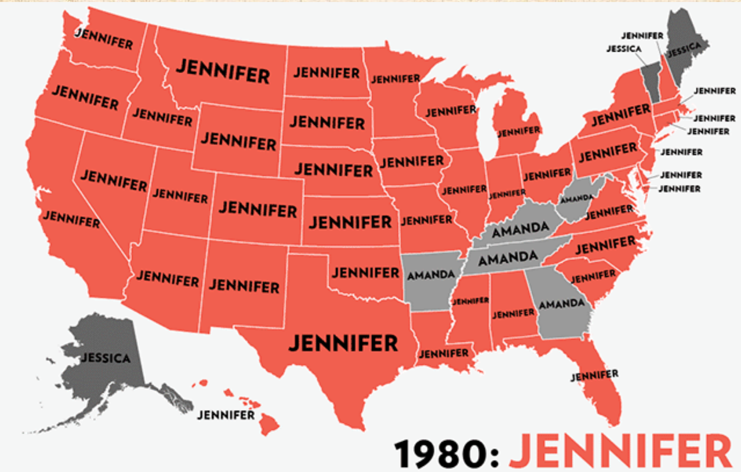

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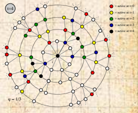

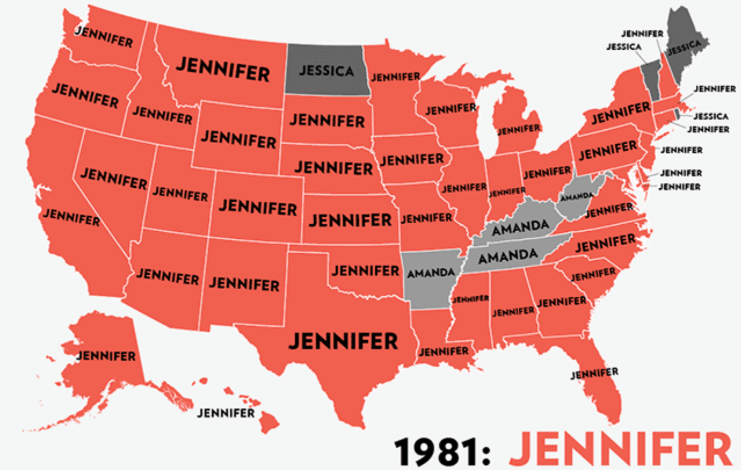

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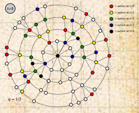

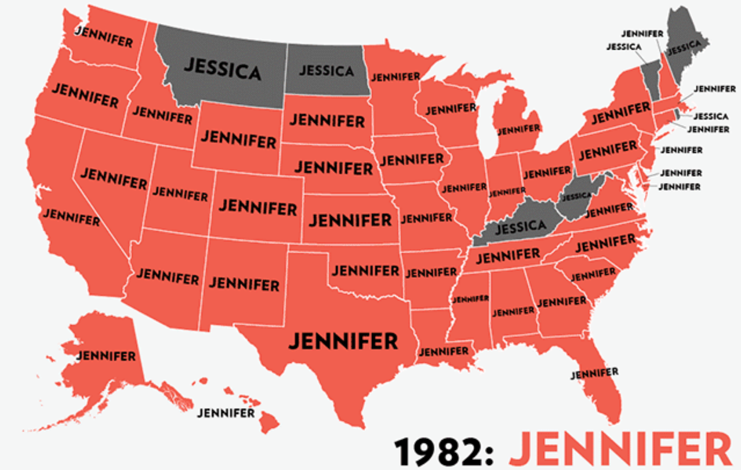

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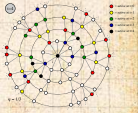

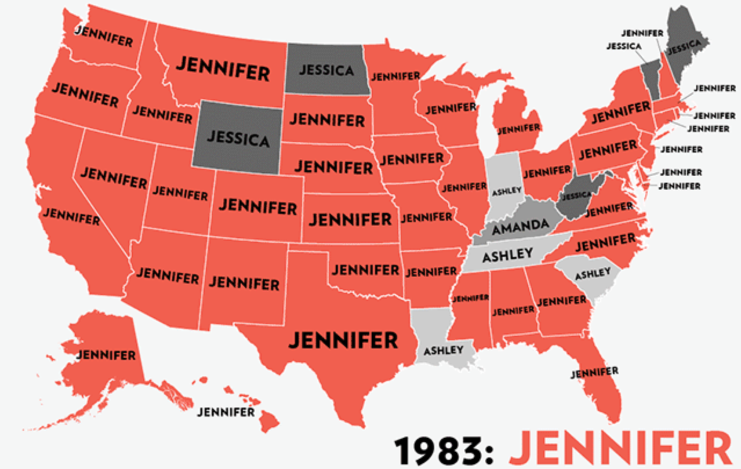

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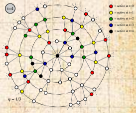

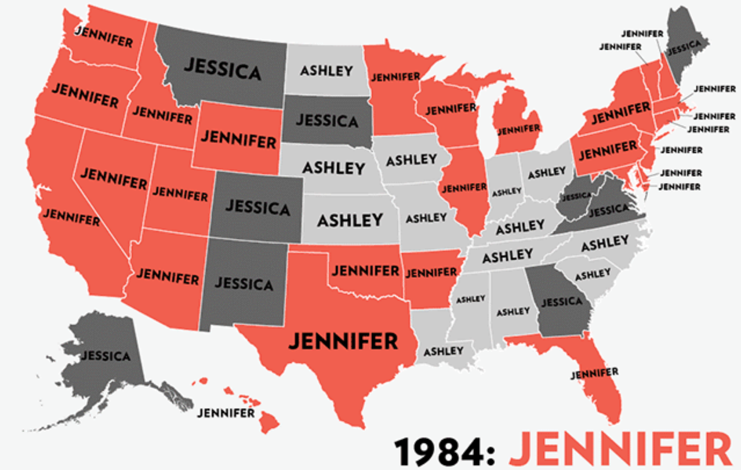

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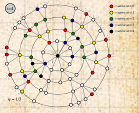

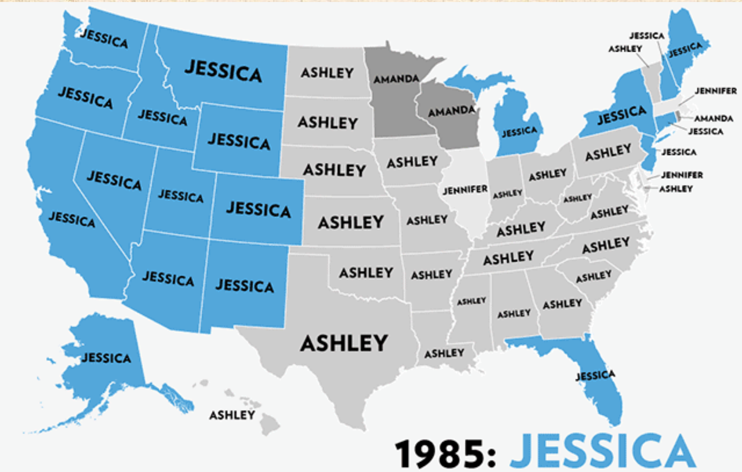

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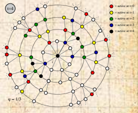

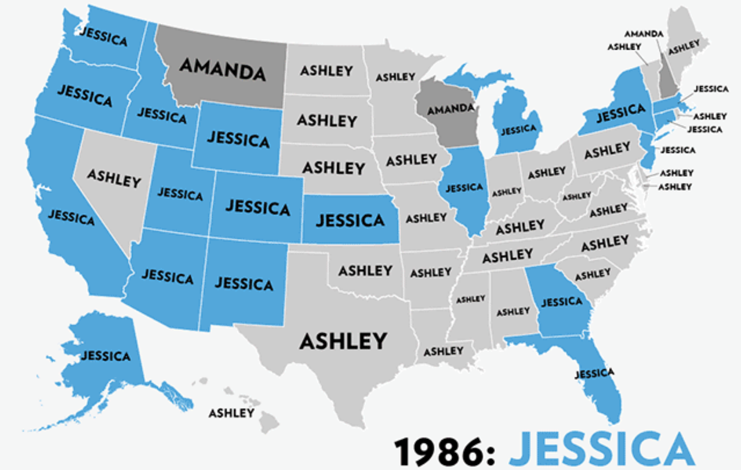

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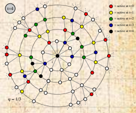

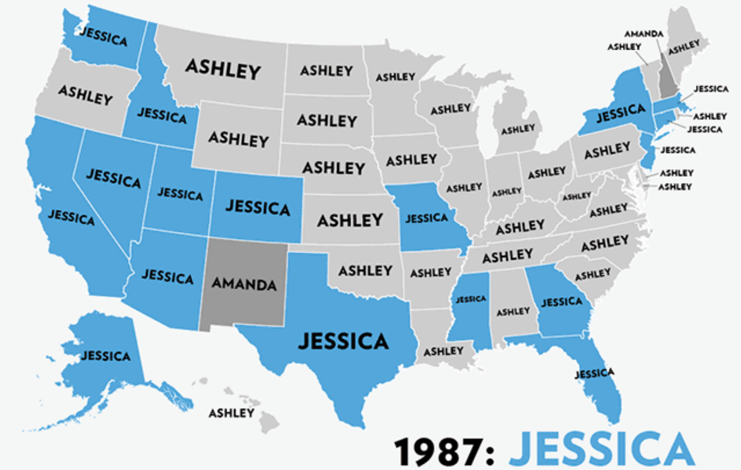

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Social Contagion Models

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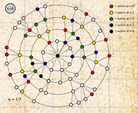

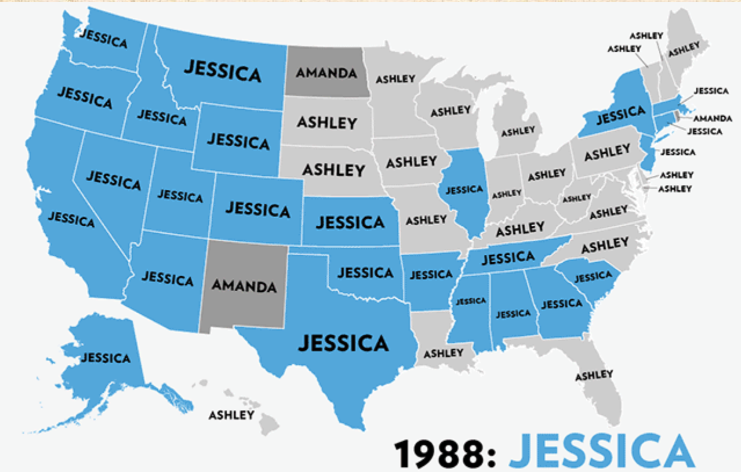

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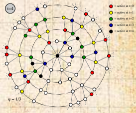

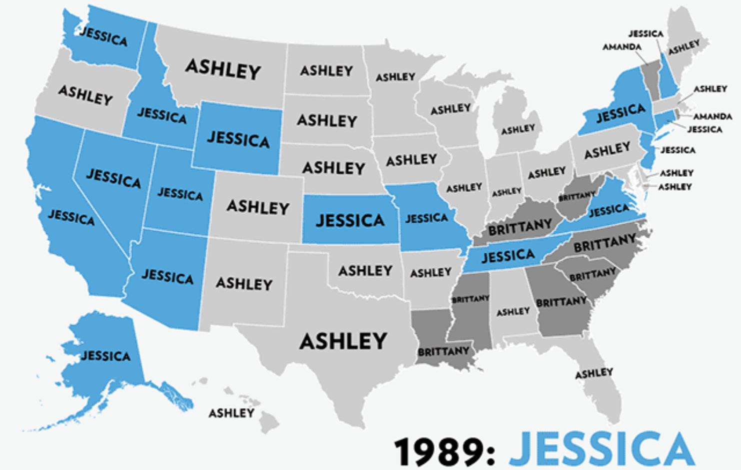

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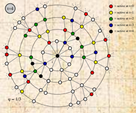

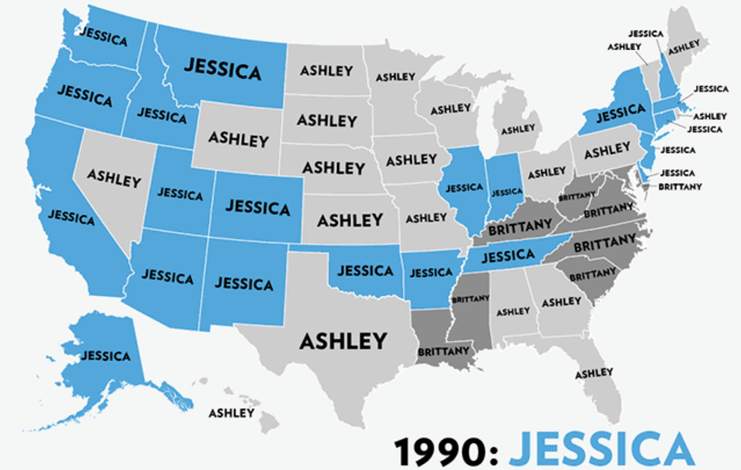

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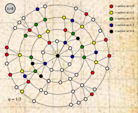

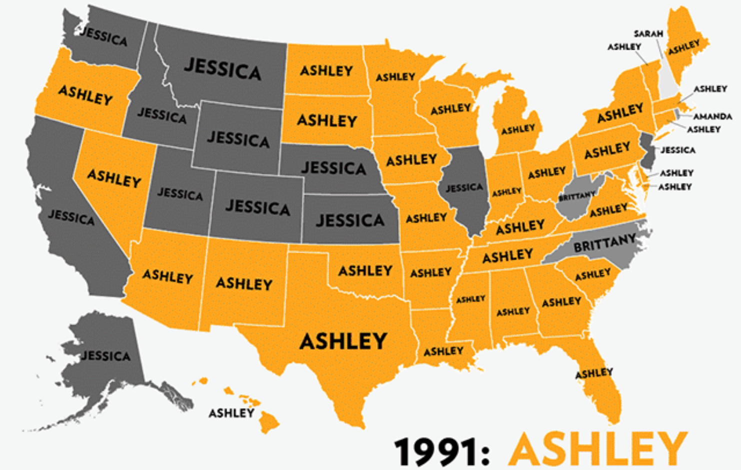

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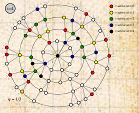

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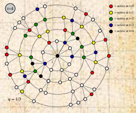

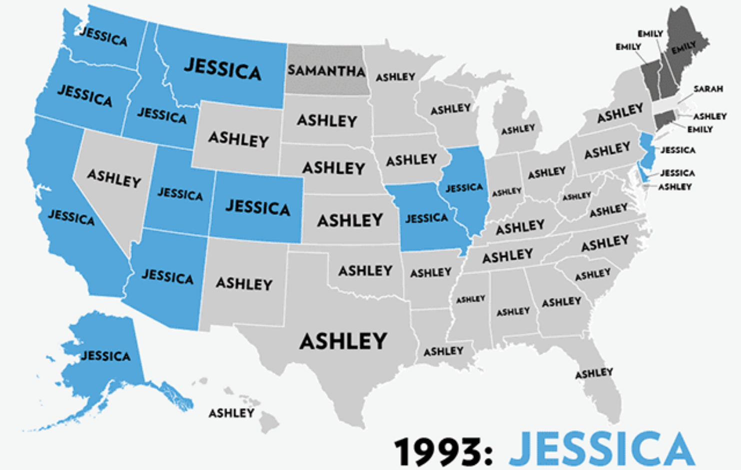

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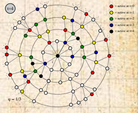

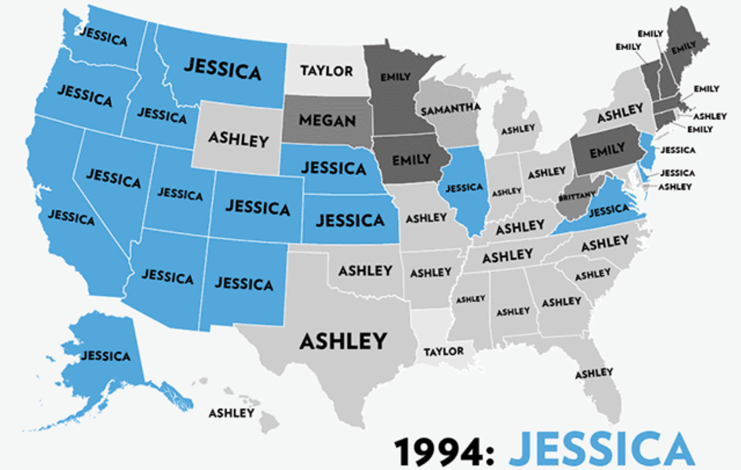

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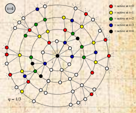

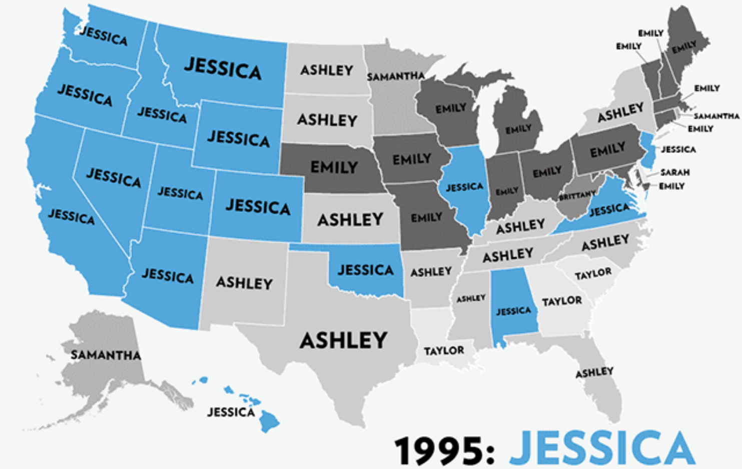

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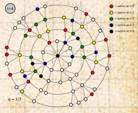

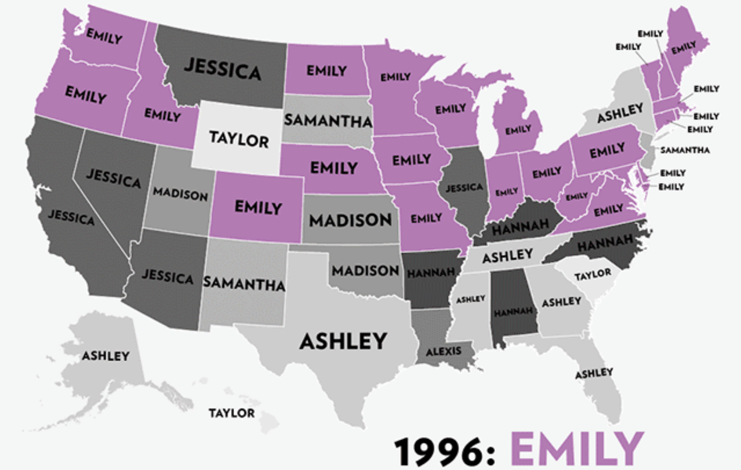

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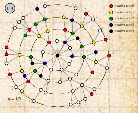

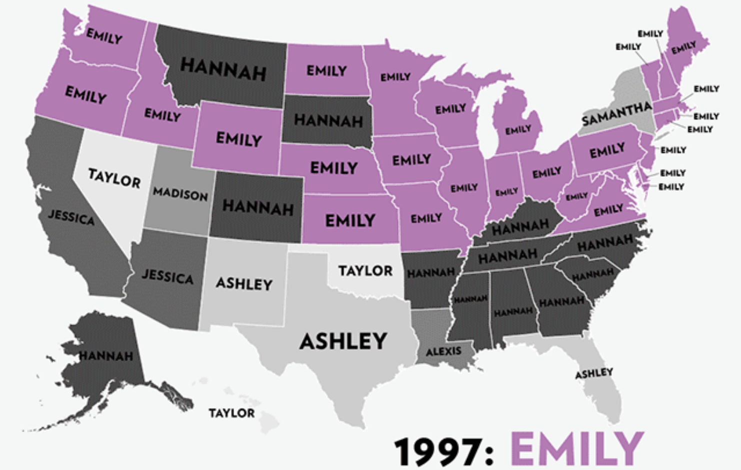

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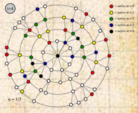

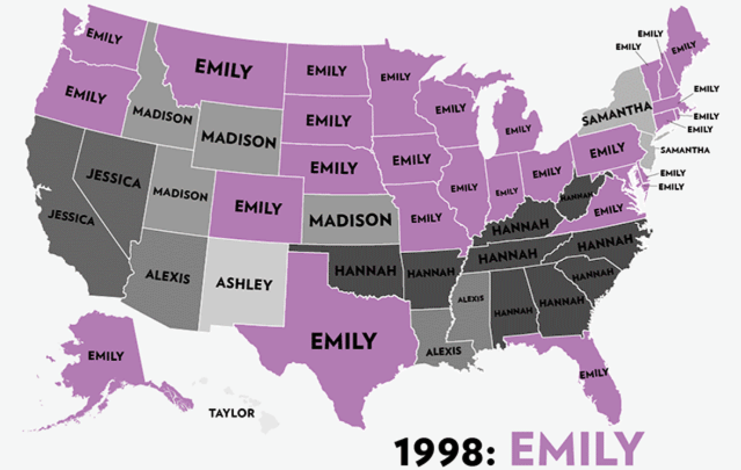

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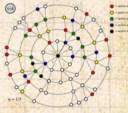

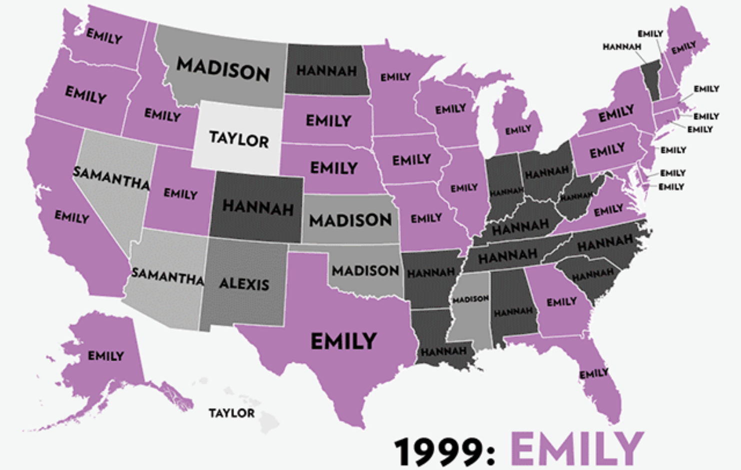

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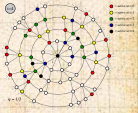

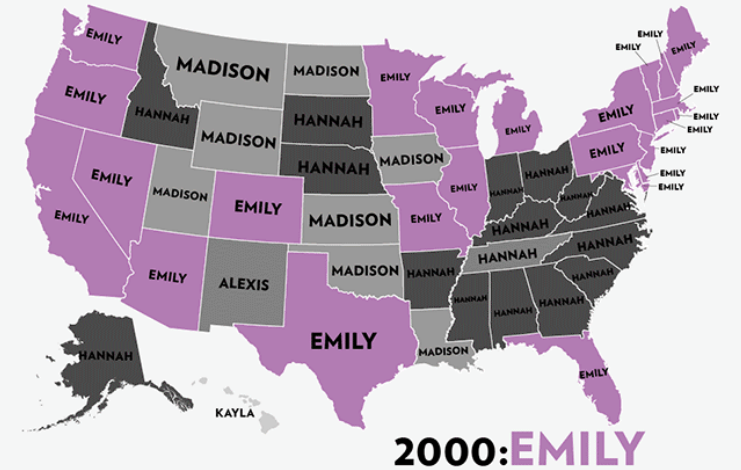

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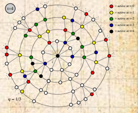

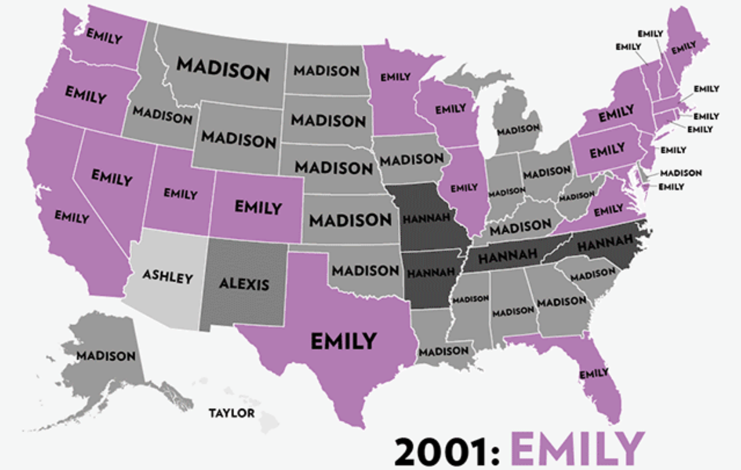

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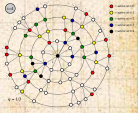

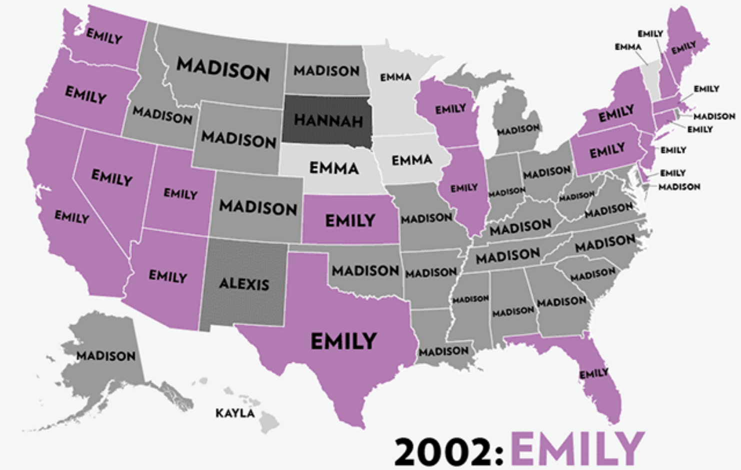

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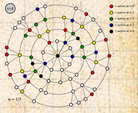

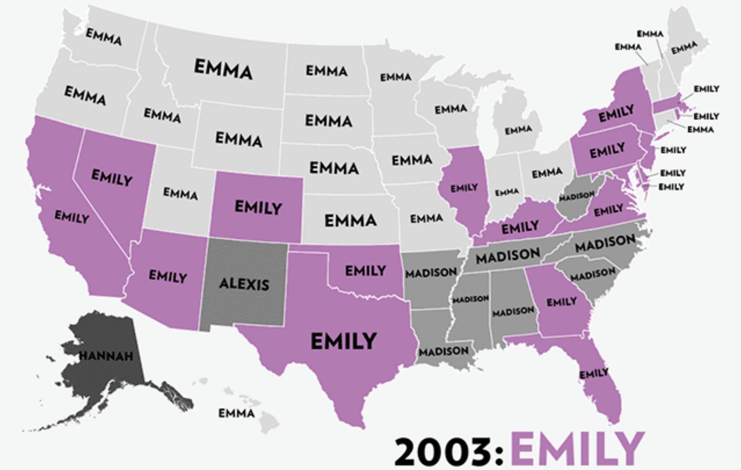

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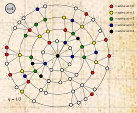

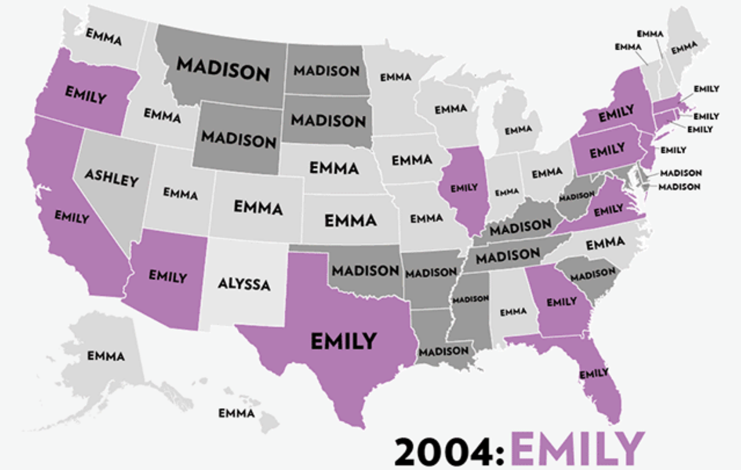

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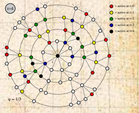

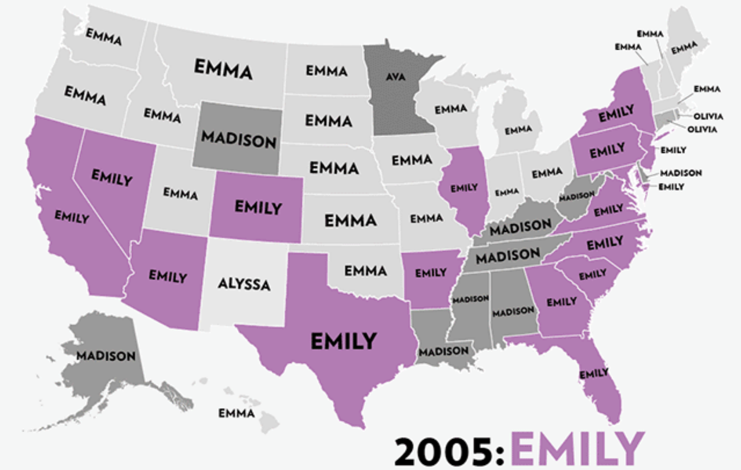

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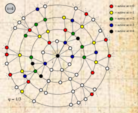

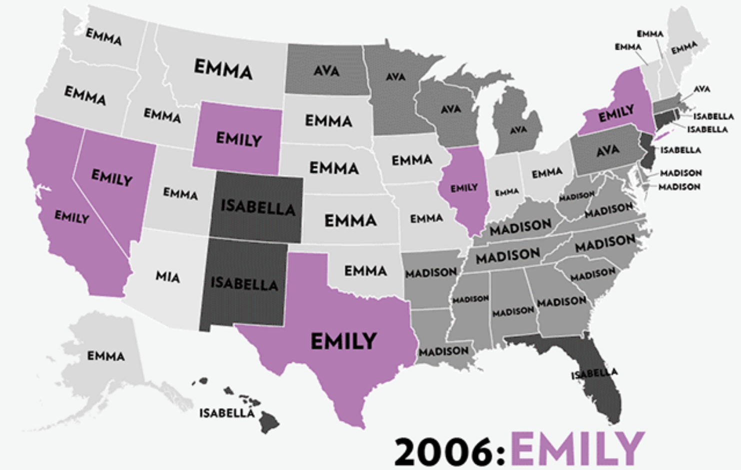

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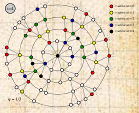

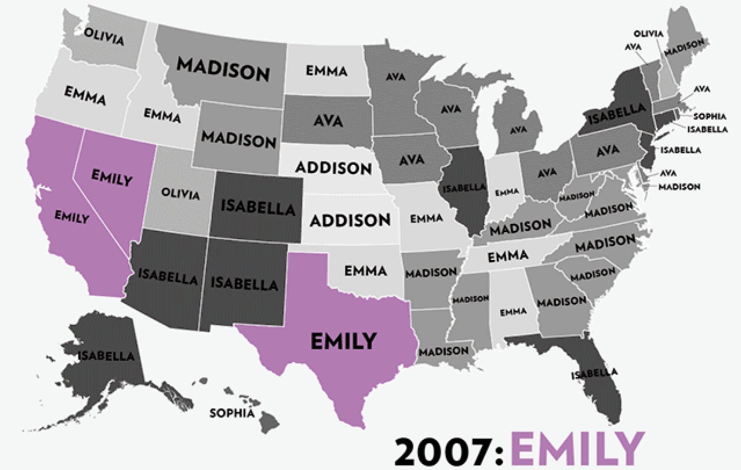

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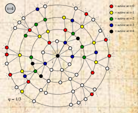

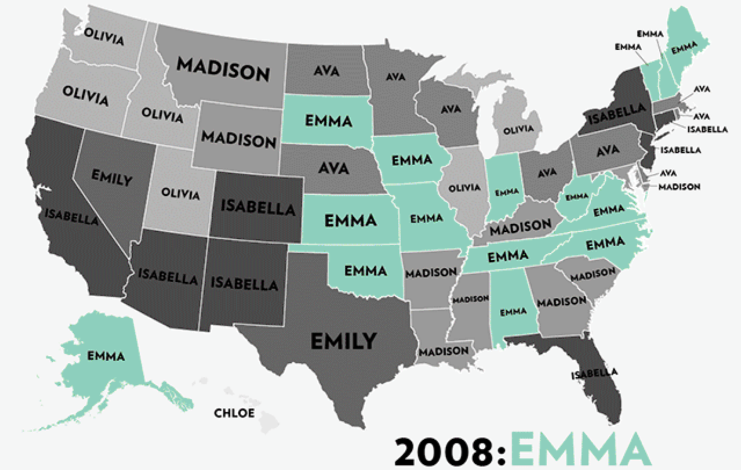

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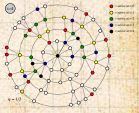

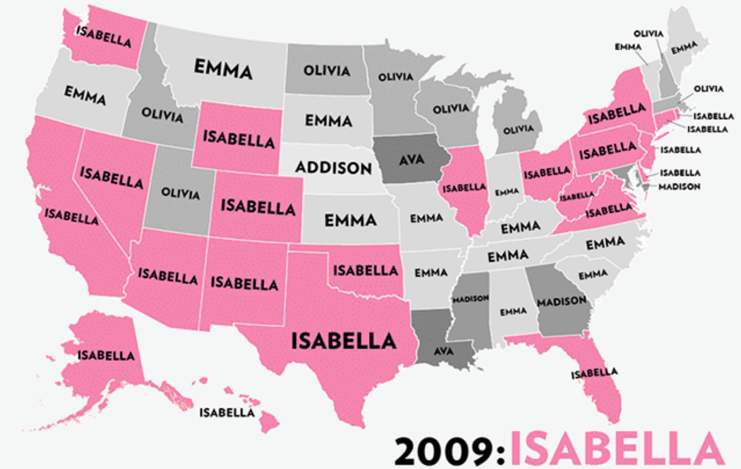

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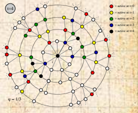

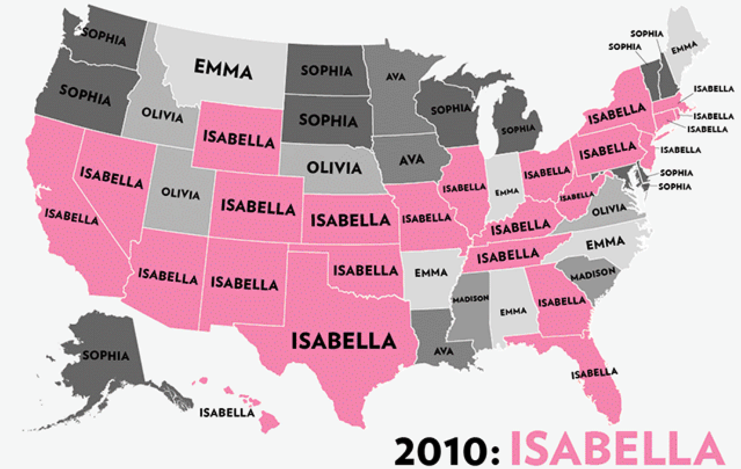

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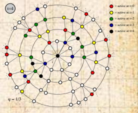

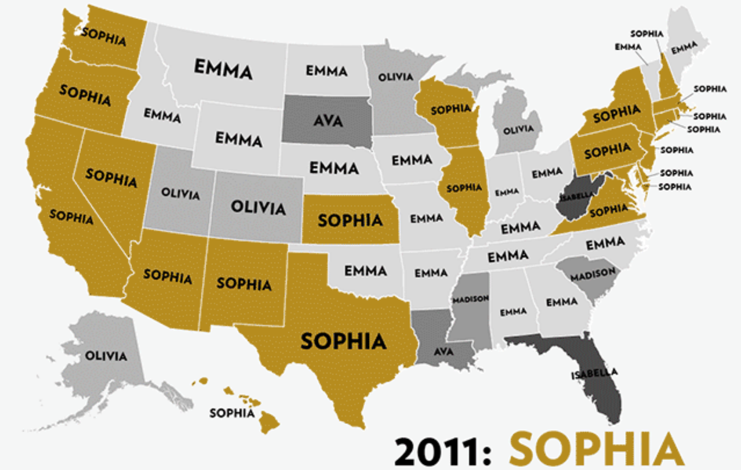

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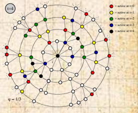

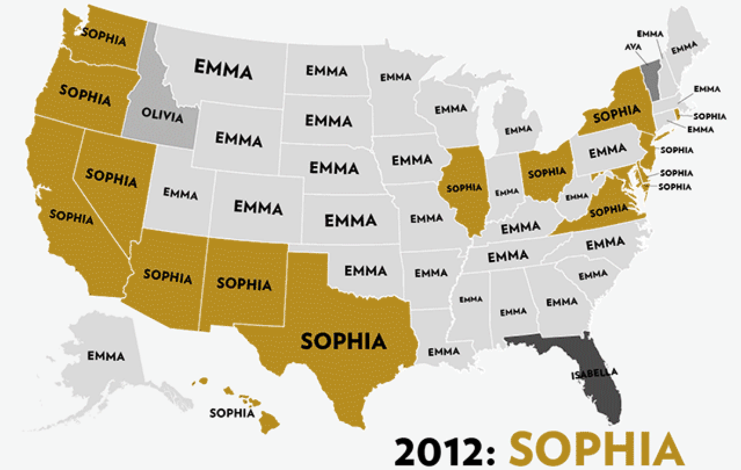

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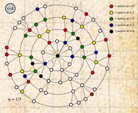
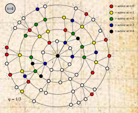
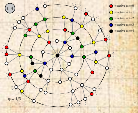


Richard Feynmann on the Social Sciences:



Sheldon Cooper on the Social Sciences:

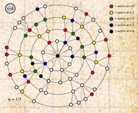


Things that spread well:

buzzfeed.com:

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

+ News ...



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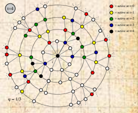
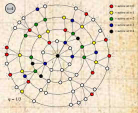
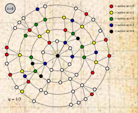


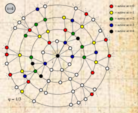
LOL + cute + fail + wtf:



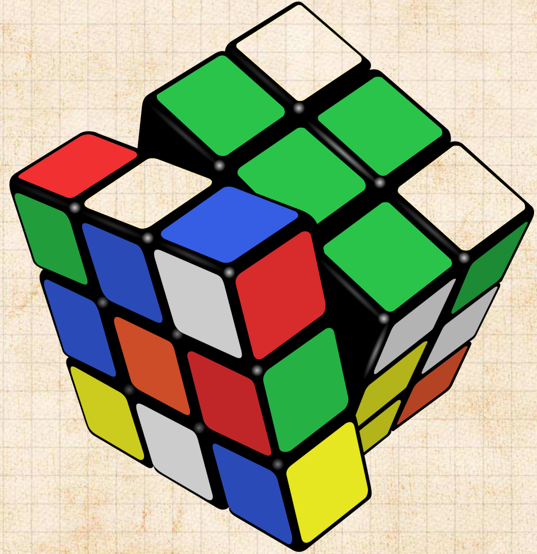
The whole lolcats thing:



Some things really stick:



wtf + geeky + omg:



Outline

Social Contagion Models

Background

Granovetter's model

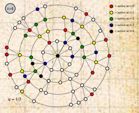
Network version

Final size

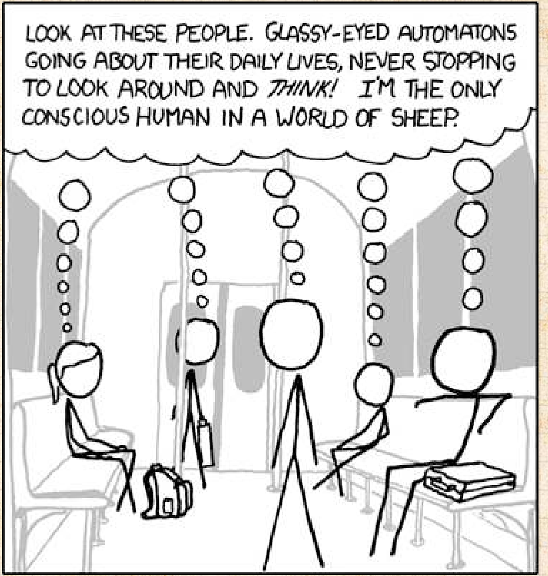
Spreading success

Groups

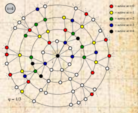
References



Why social contagion works so well:



http://xkcd.com/610/



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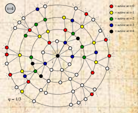


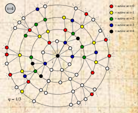
Social Contagion

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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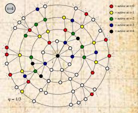

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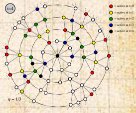

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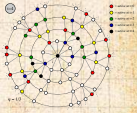
SIR and SIRS type contagion possible

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



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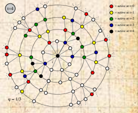
- Misframing: Appeals only to seed on exponential growth.



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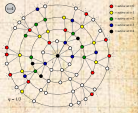

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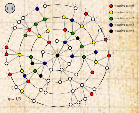
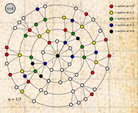


Market much?



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Evolving network stories (Christakis and Fowler):

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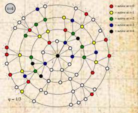

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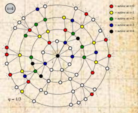

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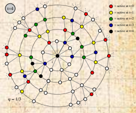

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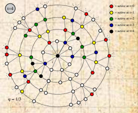

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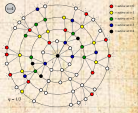


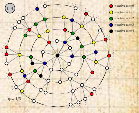
Social Contagion

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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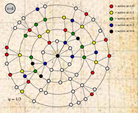

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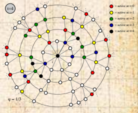

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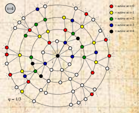

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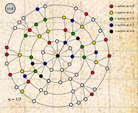

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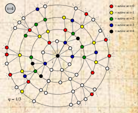

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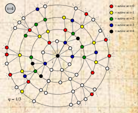

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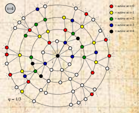

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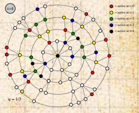

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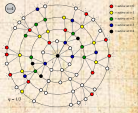
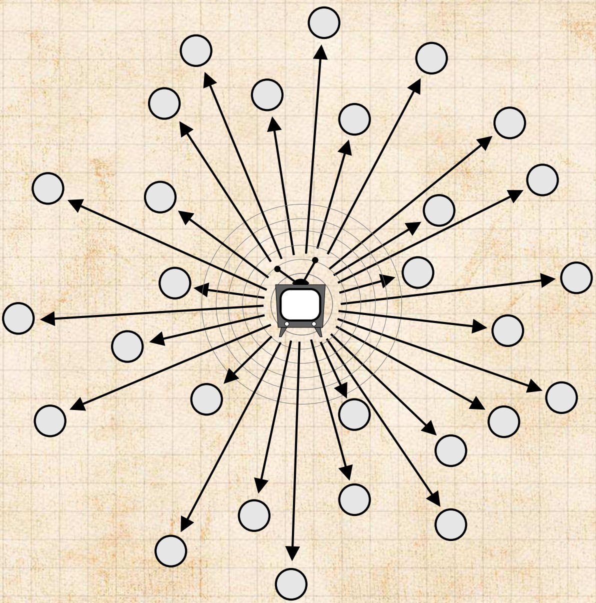
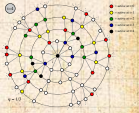
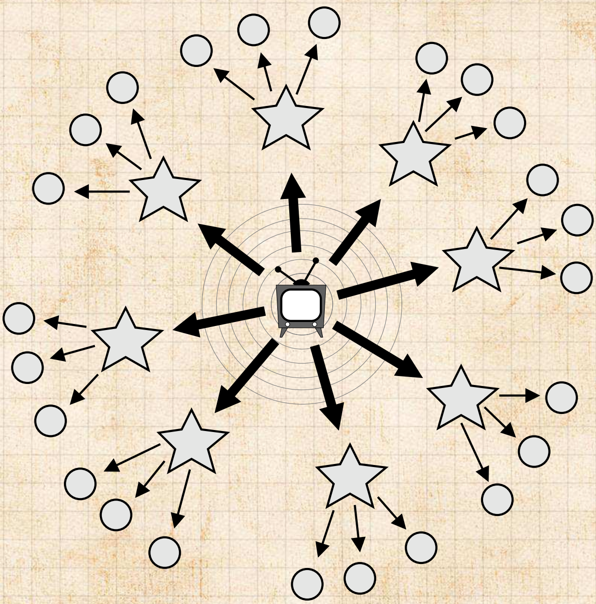


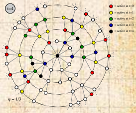
The hypodermic model of influence



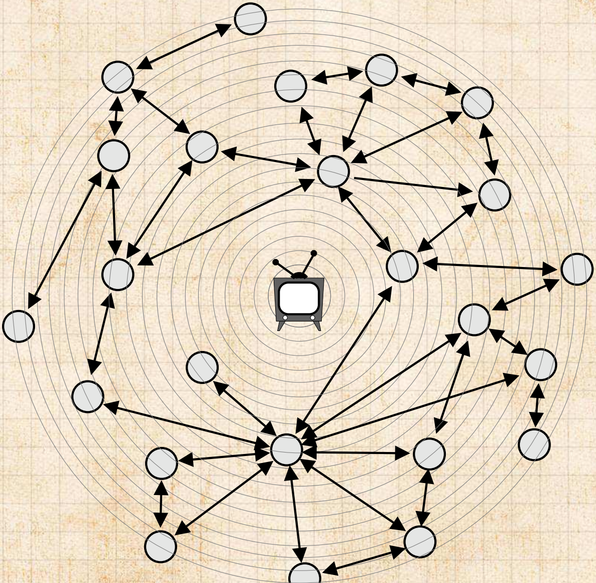


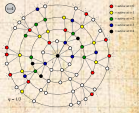
The two step model of influence [19]



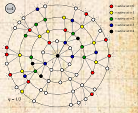


The general model of influence: the Social Wild





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).
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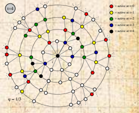
- System/group dynamics harder to understand because most of our stories are built around individuals.
- Always good to examine what is said before and after the fact ...



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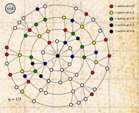

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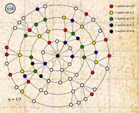

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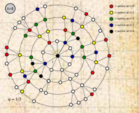

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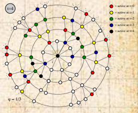

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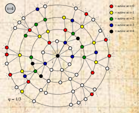

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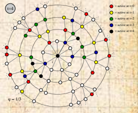

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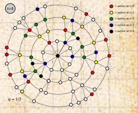

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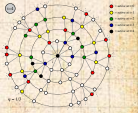

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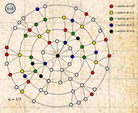
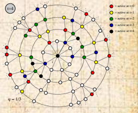


The Mona Lisa



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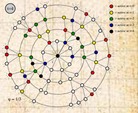

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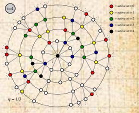

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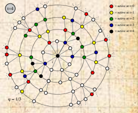

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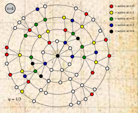

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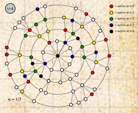
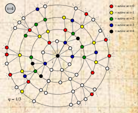


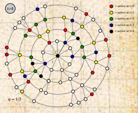
‘Tattooed Guy’ Was Pivotal in Armstrong Case [nytimes]

- “... Leogrande’s doping sparked a series of events ...”

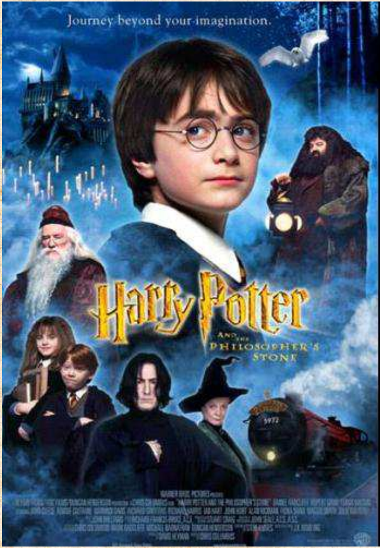


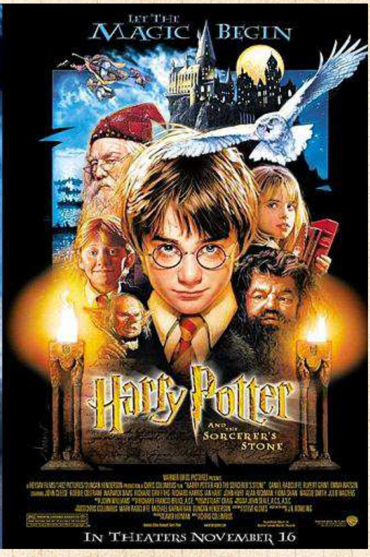
The completely unpredicted fall of Eastern Europe

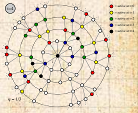
Timur Kuran: [20, 21] "Now Out of Never: The Element of Surprise in the East European Revolution of 1989"



The dismal predictive powers of editors...







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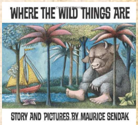

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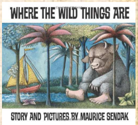

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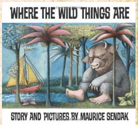

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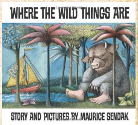

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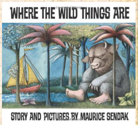

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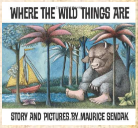

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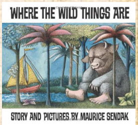

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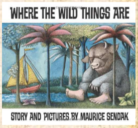

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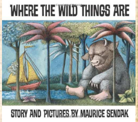

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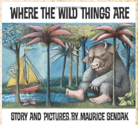

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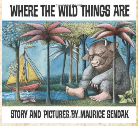

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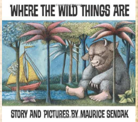

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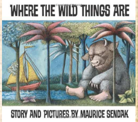

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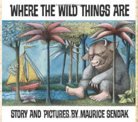

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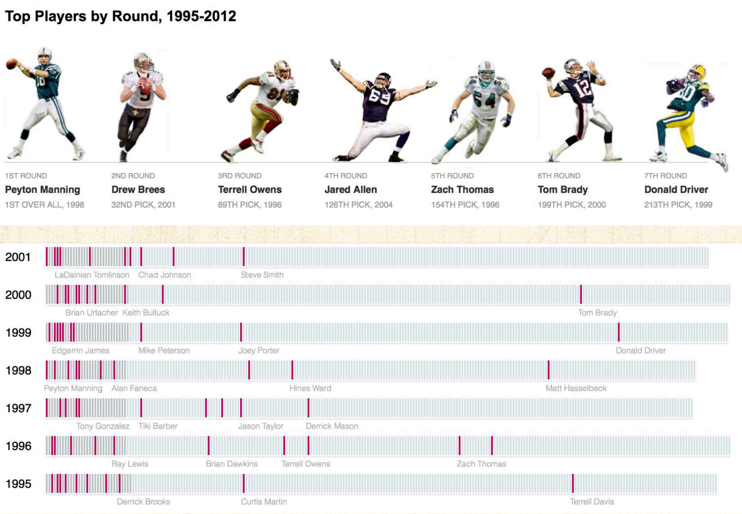
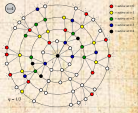


Social Contagion

Messing with social connections

- Ads based on message content
- BzzAgent
- One of Facebook's early advertising attempts: Beacon
- All of Facebook's advertising attempts.



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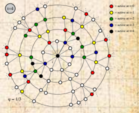

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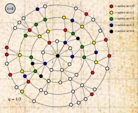

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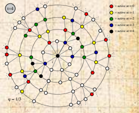

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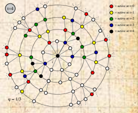

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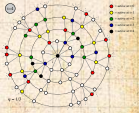

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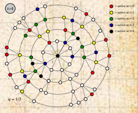

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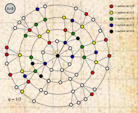

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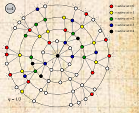

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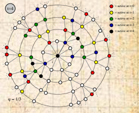

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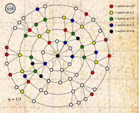

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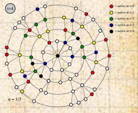

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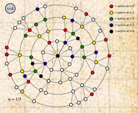

Getting others to do things for you

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

Six modes of influence:

1. Reciprocation: *The Old Give and Take… and Take*; e.g., Free samples, Hare Krishnas.
2. Commitment and Consistency: *Hobgoblins of the Mind*; e.g., Hazing.
3. Social Proof: *Truths Are Us*; e.g., Jonestown, Kitty Genovese (contested).
4. Liking: *The Friendly Thief*; e.g., Separation into groups is enough to cause problems.
5. Authority: *Directed Deference*; e.g., Milgram's obedience to authority experiment.
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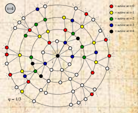
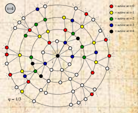


Social contagion

- 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)
- Conspicuous Destruction (Potlatch)



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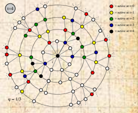

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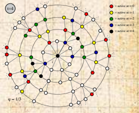

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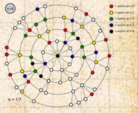

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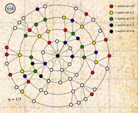

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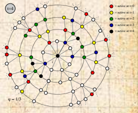


THE SUN
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THE WELL OF SCALES
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THE UNEXPECTED TRANSFIGURATION
THE RICH GET RICHER
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THE EMERGENCE OF STORIES
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THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE NETWORKS COMPLEX
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THE ARK OF THE RANDOM NETWORK
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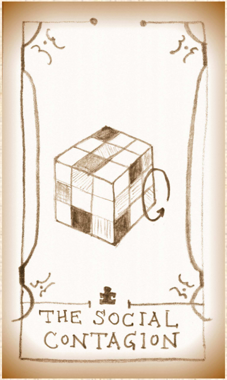
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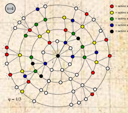

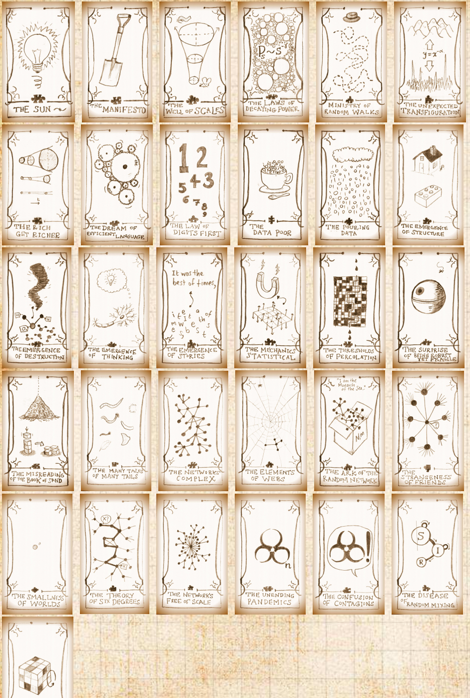
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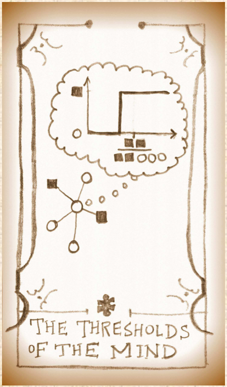
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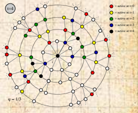

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  - Idea of thresholds
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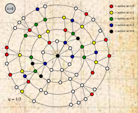

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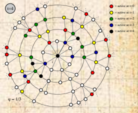

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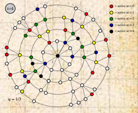

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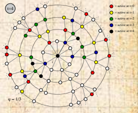

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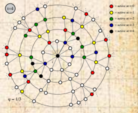

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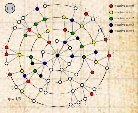

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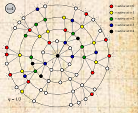

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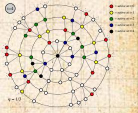
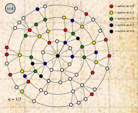


Social contagion models

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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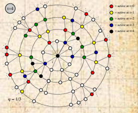

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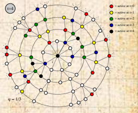

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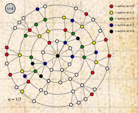

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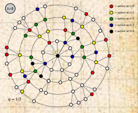

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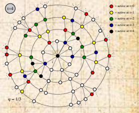

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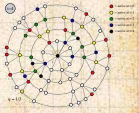

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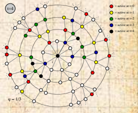

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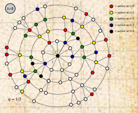

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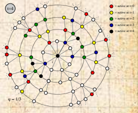
Some possible origins of thresholds:

- 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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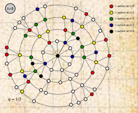

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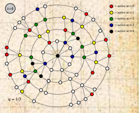

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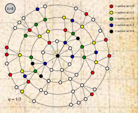

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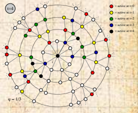

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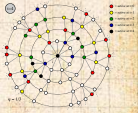

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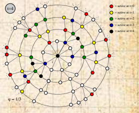
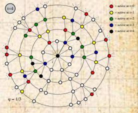


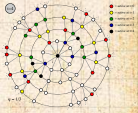
Neural reboot (NR):

Shareworthy interlude

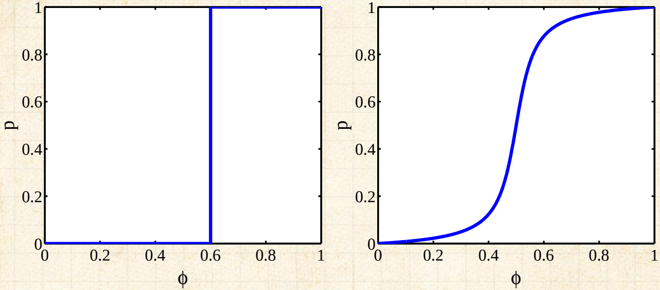
https://www.youtube.com/v/LL2GQrvbb1k?rel=0



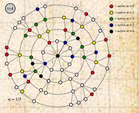
Outline



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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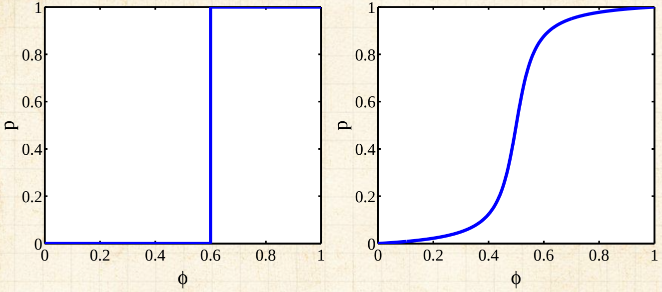

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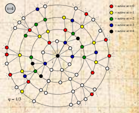

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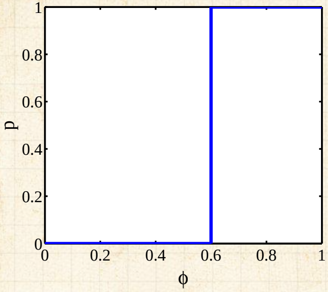

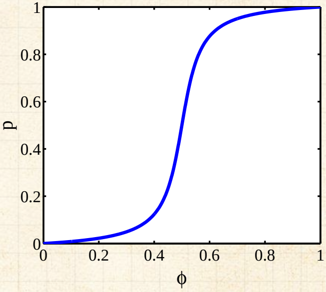

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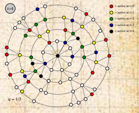
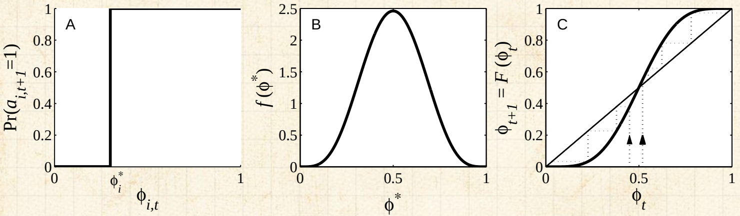
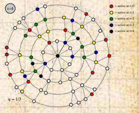


Threshold models

Action based on perceived behavior of others:



- Two states: S and I.
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Discrete time update (strong assumption!)
- This is a Critical mass model



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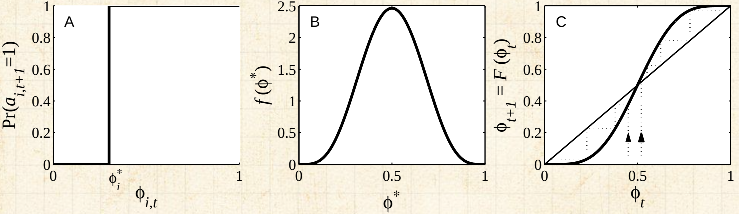

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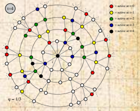

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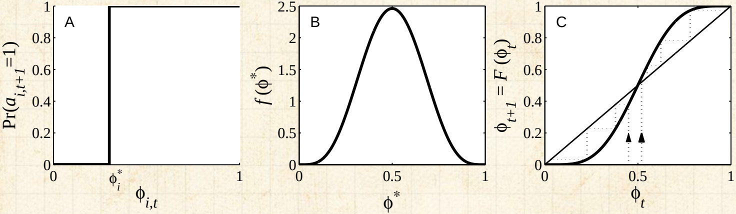

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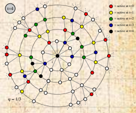
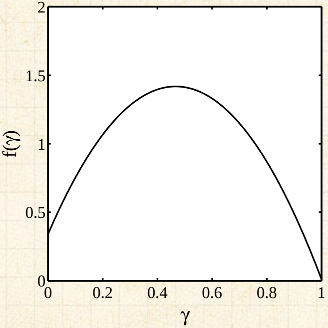
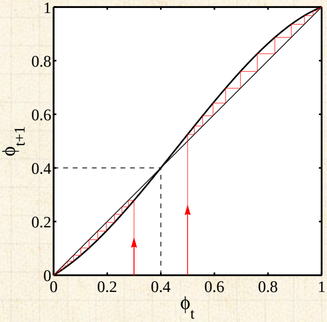
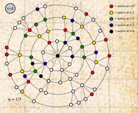


Threshold models

Another example of critical mass model:

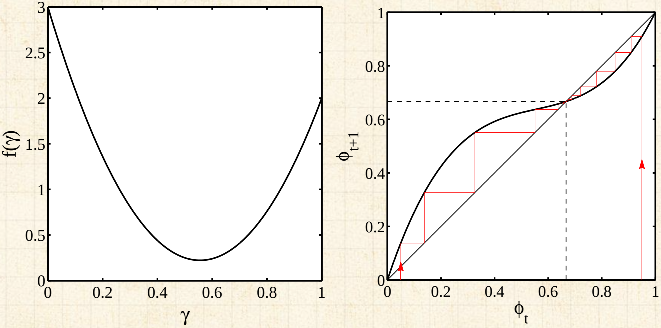


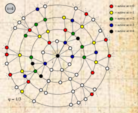




Threshold models

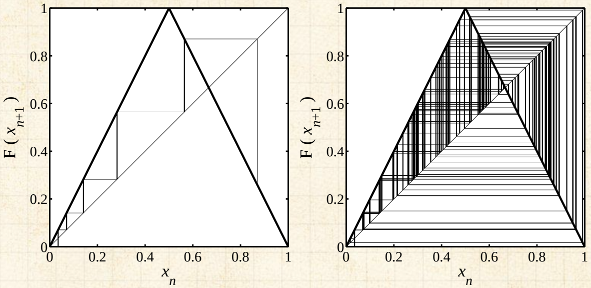
Example of single stable state model:



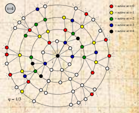


Threshold models

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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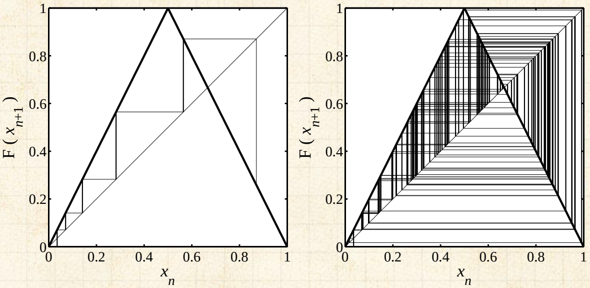

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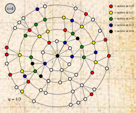

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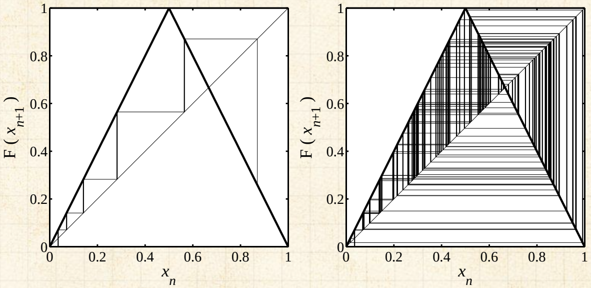

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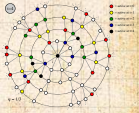
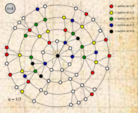


Threshold models—Nutshell

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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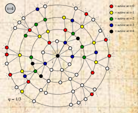

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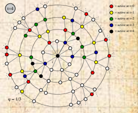

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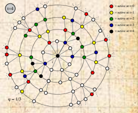

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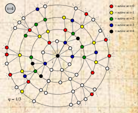

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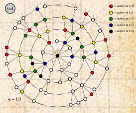

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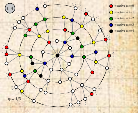

Many years after Granovetter and Soong's work:

- "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:

- "Seed size strongly affects cascades on random networks" [14]
  Gleeson and Cahalane, Phys. Rev. E, 2007.
- "Direct, phyiscally motivated derivation of the contagion condition for spreading processes on generalized random networks" [10] Dodds, Harris, and Payne, Phys. Rev. E, 2011
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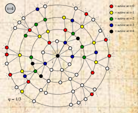

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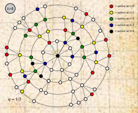

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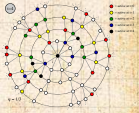

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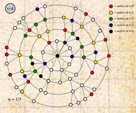
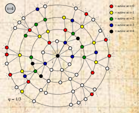


Threshold model on a network

- 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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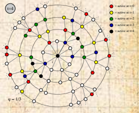

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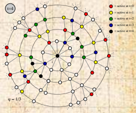

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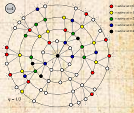

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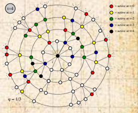

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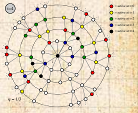

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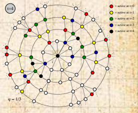

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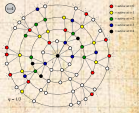

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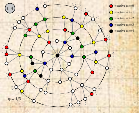

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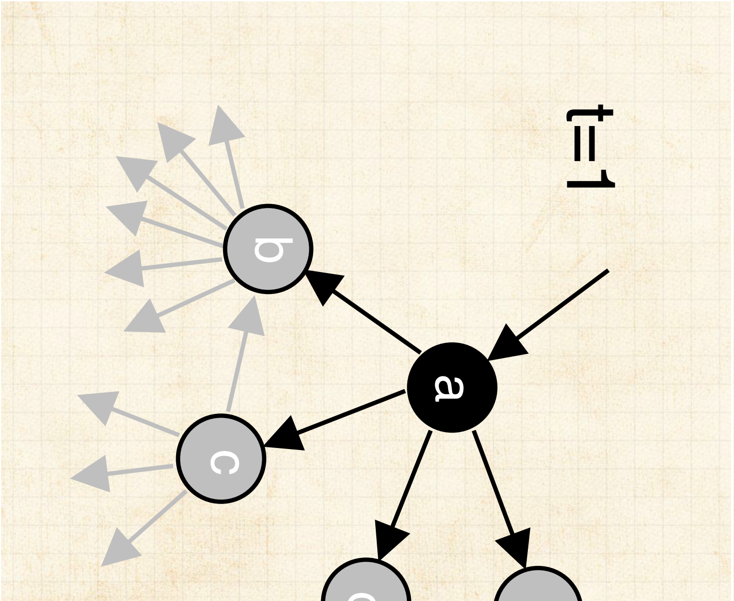

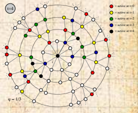

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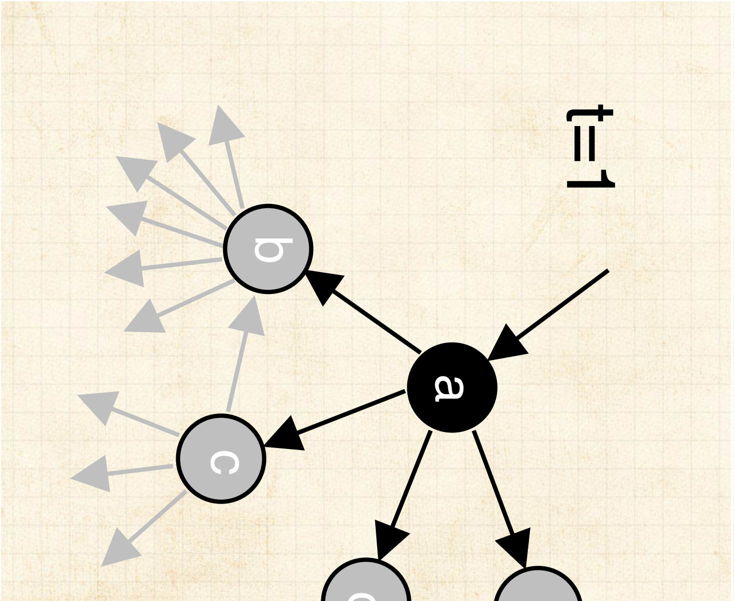

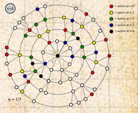

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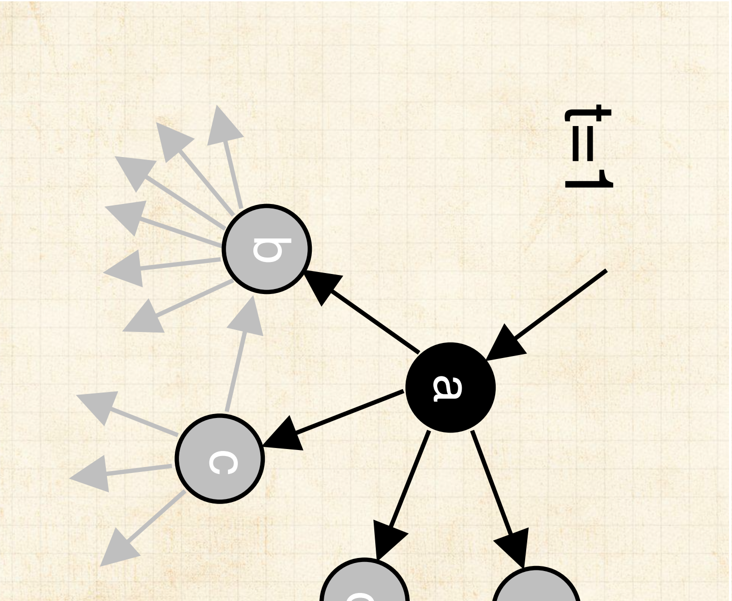
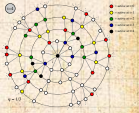




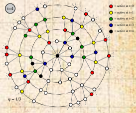
Snowballing

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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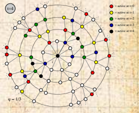

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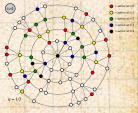

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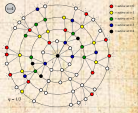

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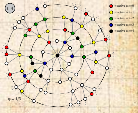

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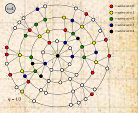

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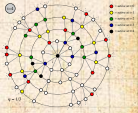
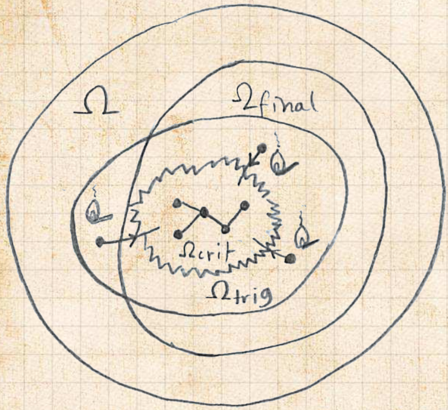
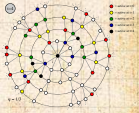


Example random network structure:



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

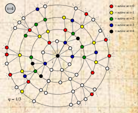
$\Omega_{crit} \subset \Omega_{trig}$; $\Omega_{crit} \subset \Omega_{final}$; and $\Omega_{trig}, \Omega_{final} \subset \Omega$.



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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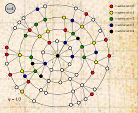

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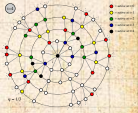

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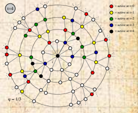


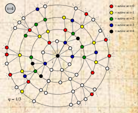
The most gullible

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 $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [26]
- Cluster of vulnerables = critical mass
- Network story: 1 node → critical mass → everyone.



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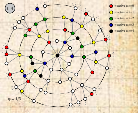

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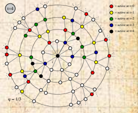

The UNIVERSITY of VERMONT

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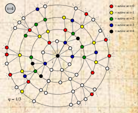

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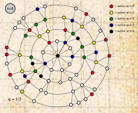

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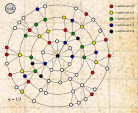

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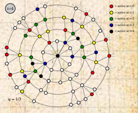


Cascade condition

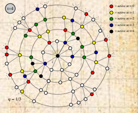
Back to following a link:

- 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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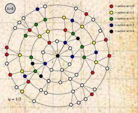

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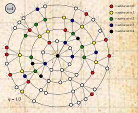

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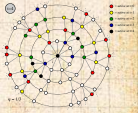

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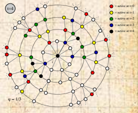


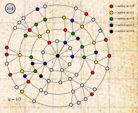
Cascade condition

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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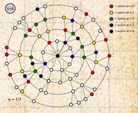

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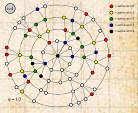

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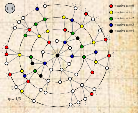

Cascade condition

Putting things together:

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

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

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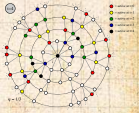

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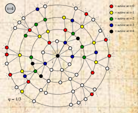

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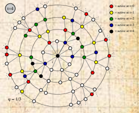

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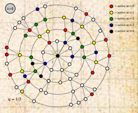
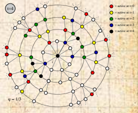


Cascade condition

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

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

- β_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: $\beta_k = \beta$

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

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

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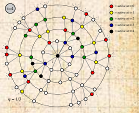

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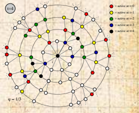

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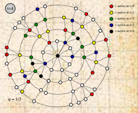

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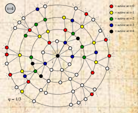

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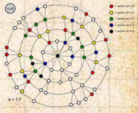
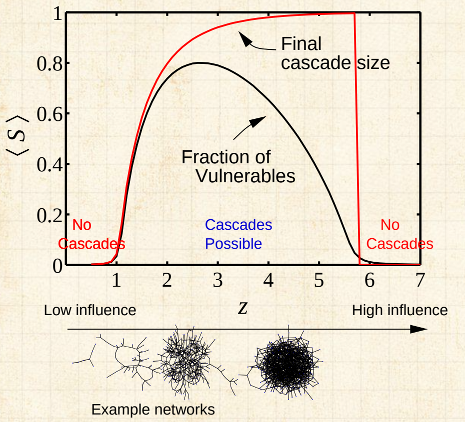


Cascades on random networks



- Cascades occur only if size of max vulnerable cluster > 0.
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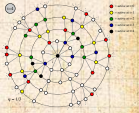
- 'Ignorance' facilitates spreading.



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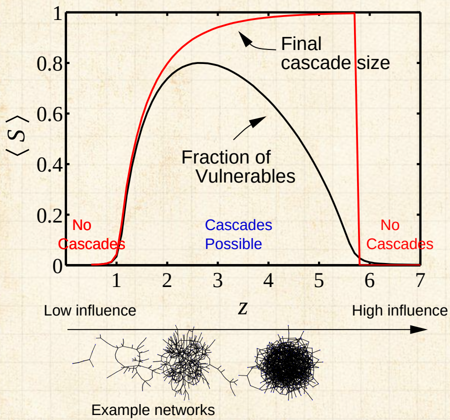

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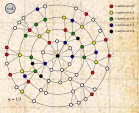

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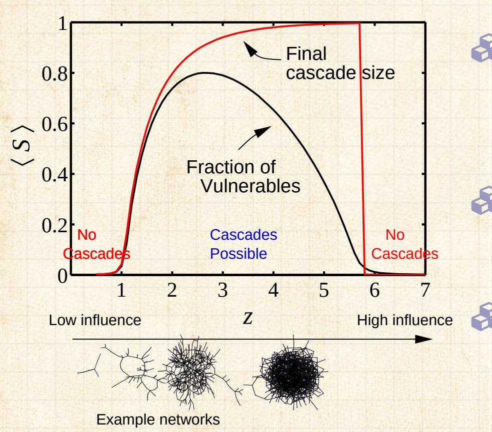

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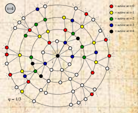
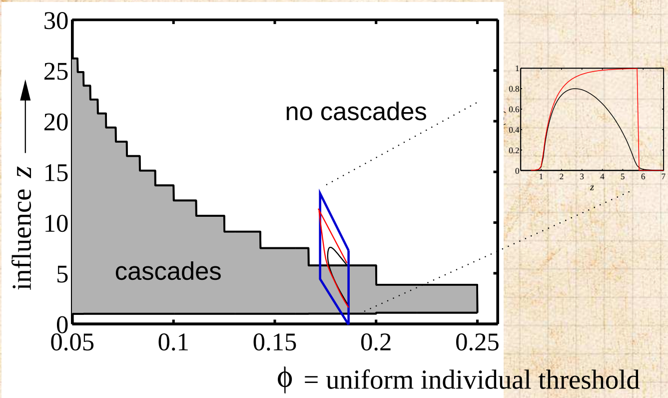
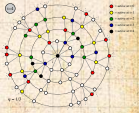


Cascade window for random networks



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



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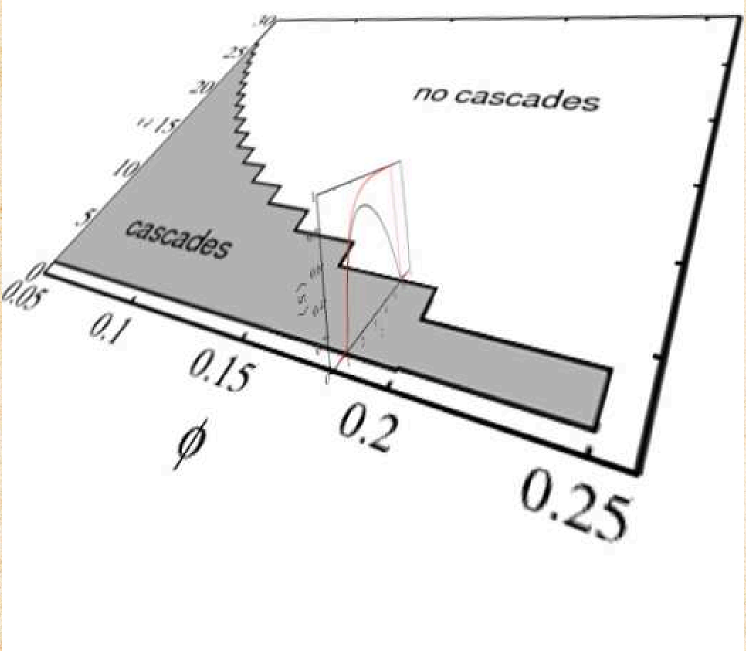
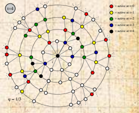
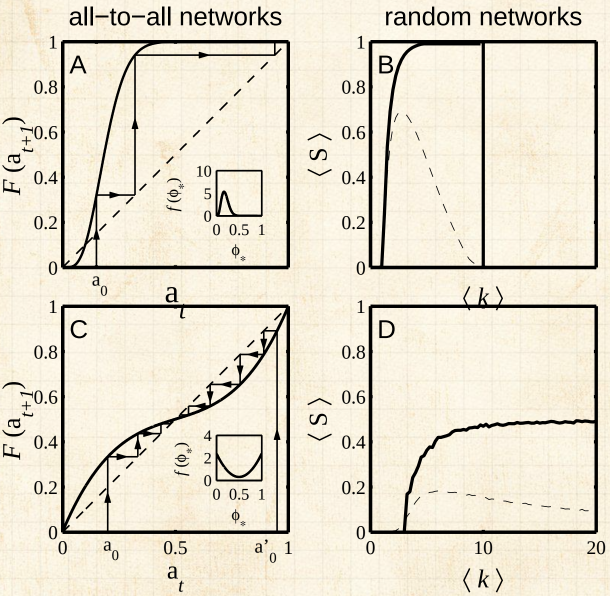
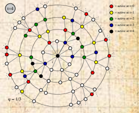




All-to-all versus random networks





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.
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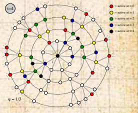
   Cascades are possible in "Cascade window."



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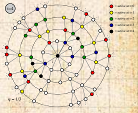

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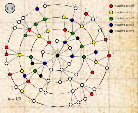

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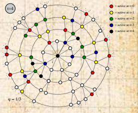


Outline

Social Contagion Models

Background

Granovetter's model

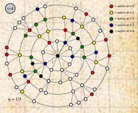
Network version

Final size

Spreading success

Groups

References



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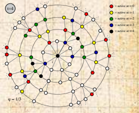

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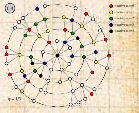

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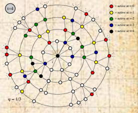

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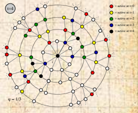

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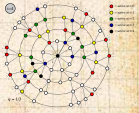

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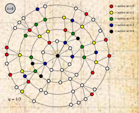

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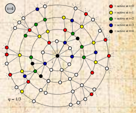

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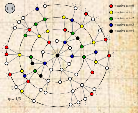

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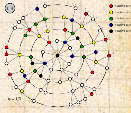

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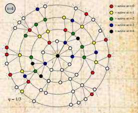

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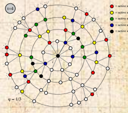

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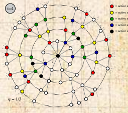

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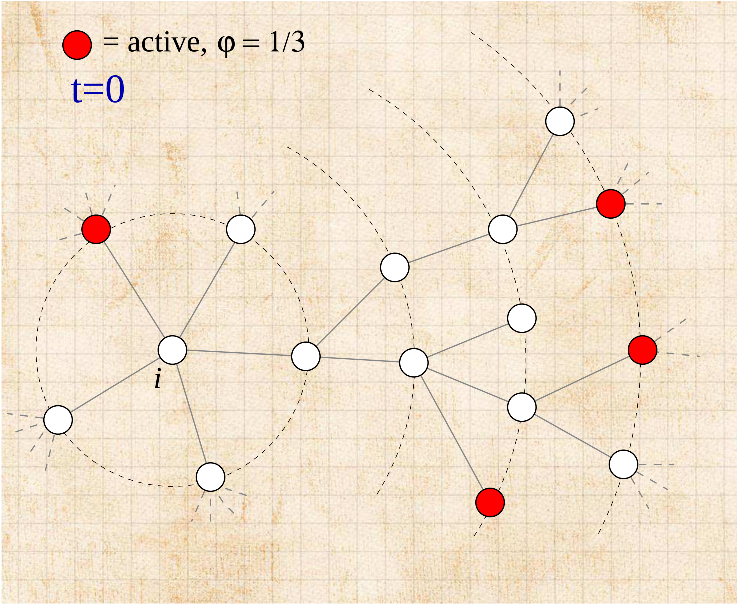

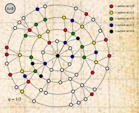

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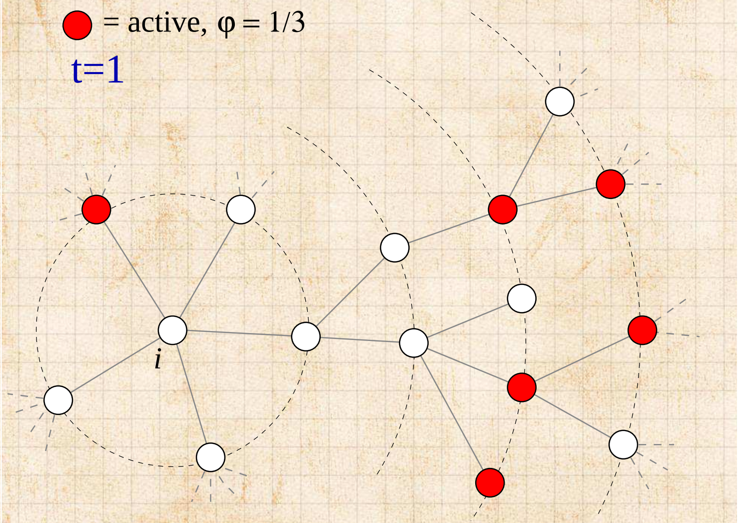

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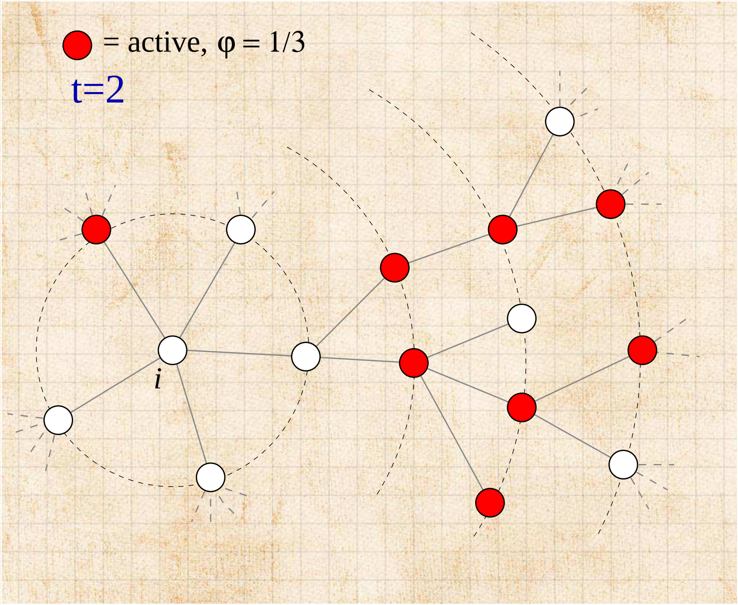

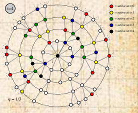

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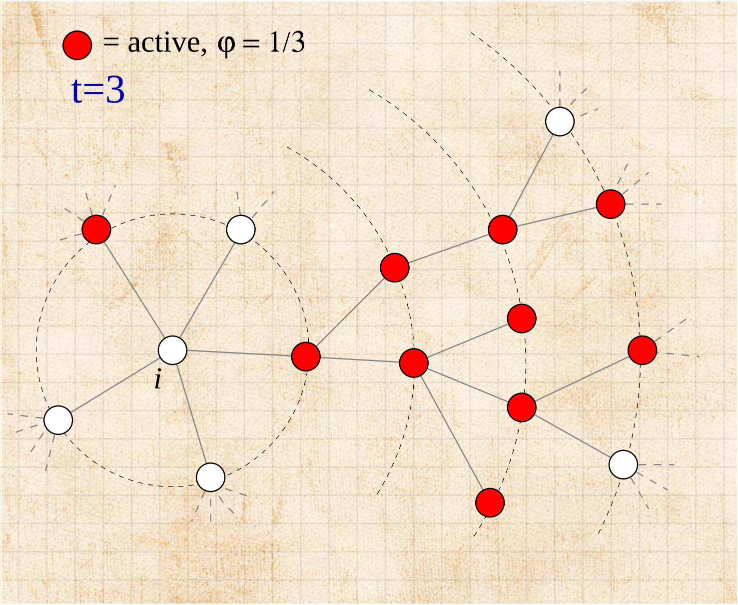

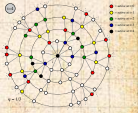

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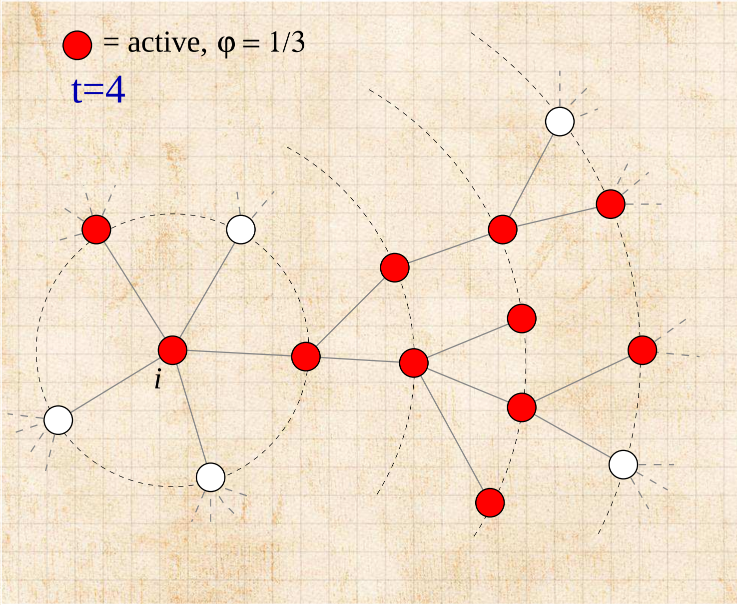

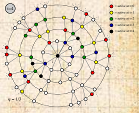

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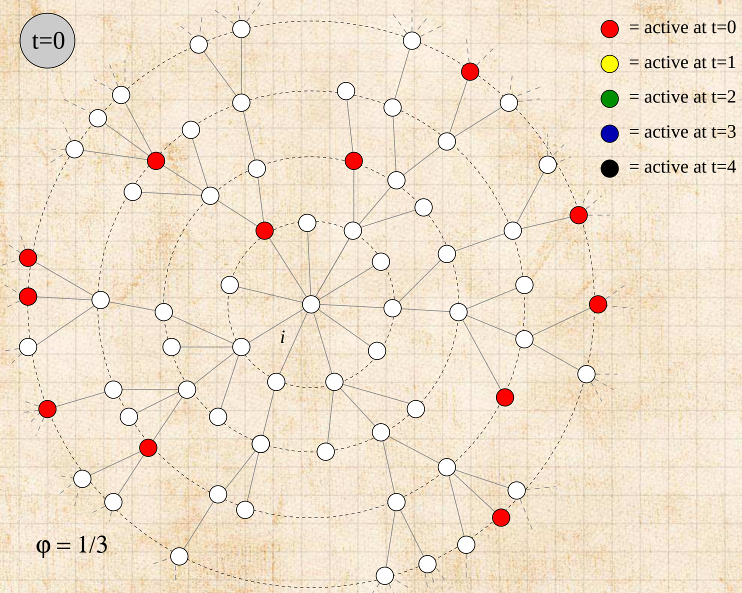

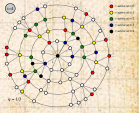

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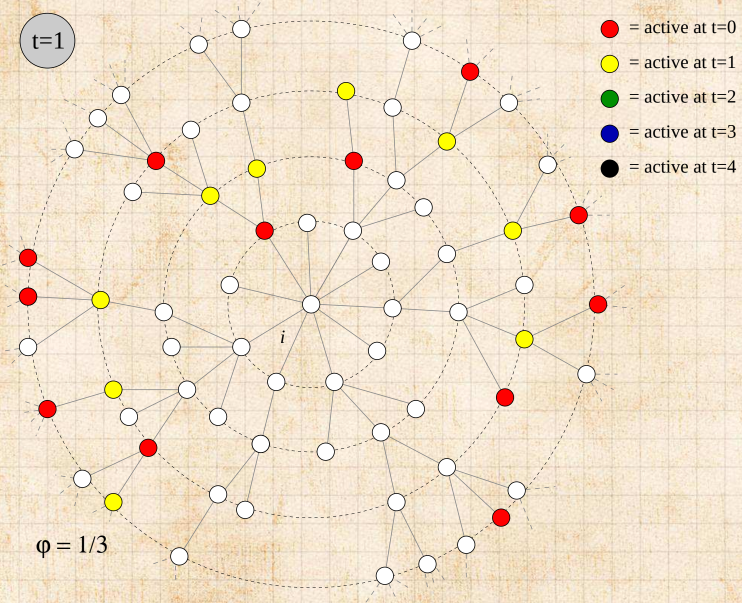

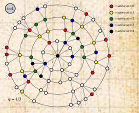

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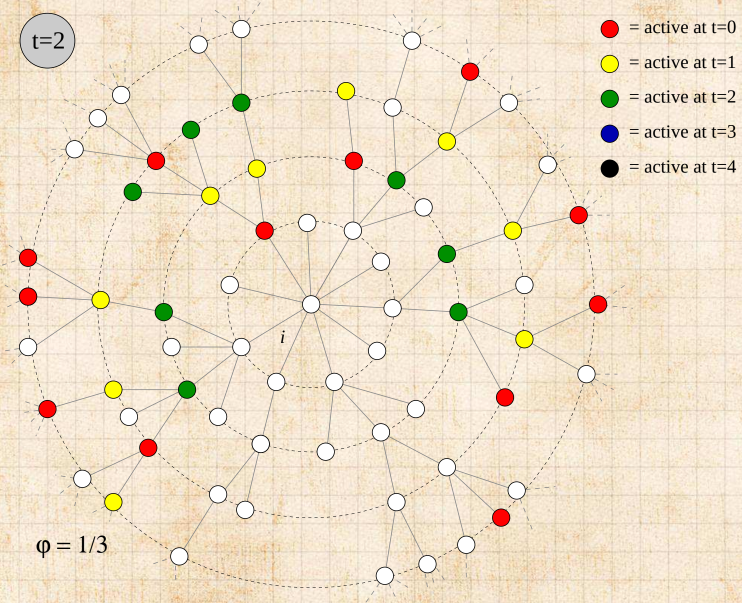

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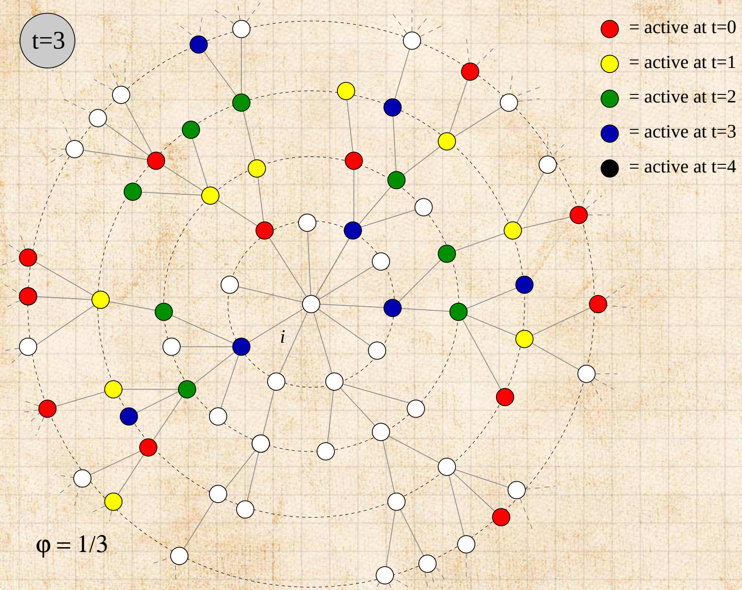

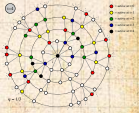

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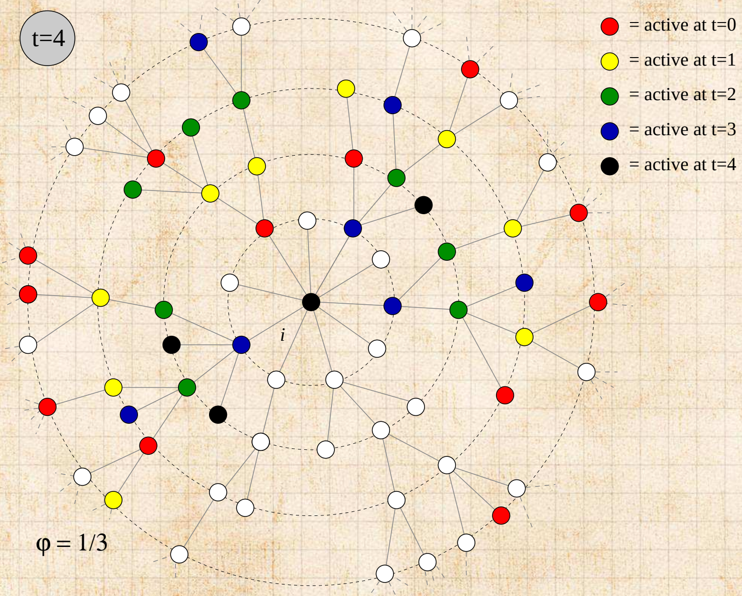

Expected size of spread

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.
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- We can in fact determine $\mathbf{Pr}$(node of degree k switching on at time t).
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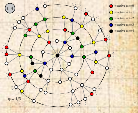

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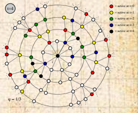

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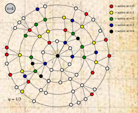

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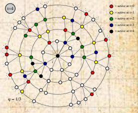

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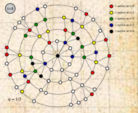

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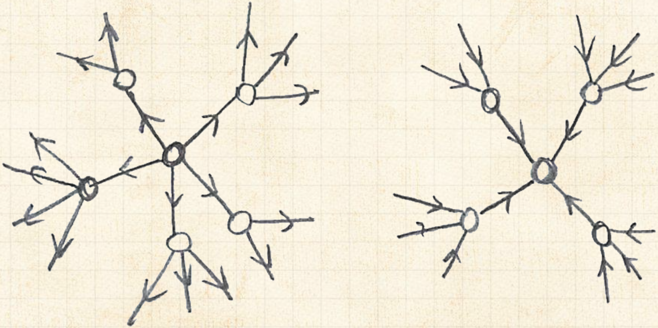
Expected size of spread

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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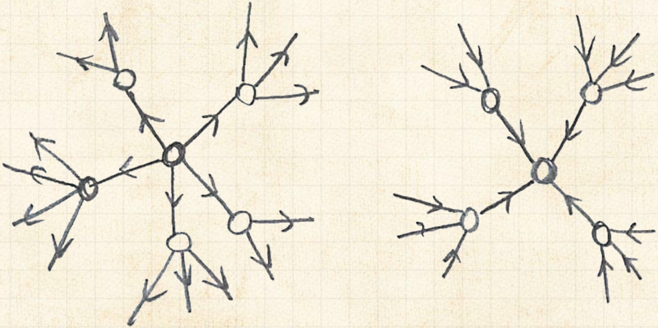

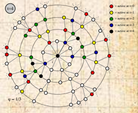

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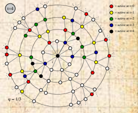

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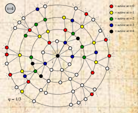

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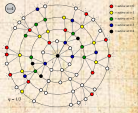

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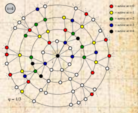

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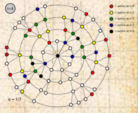

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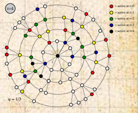

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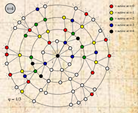

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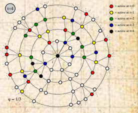

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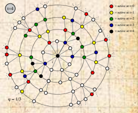

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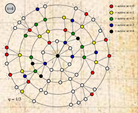

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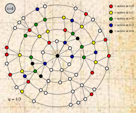

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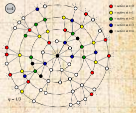

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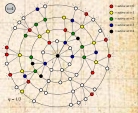

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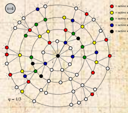

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First connect θ_0 to θ_1:

- $\theta_1 = \phi_0 +$

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

- $\frac{kP_k}{\langle k\rangle} = R_k$ = $\mathbf{Pr}$ (edge connects to a degree k node).
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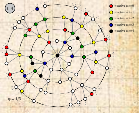

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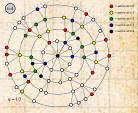


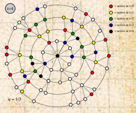
Expected size of spread

Two pieces: edges first, and then nodes

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

   with $\theta_0 = \phi_0$.

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



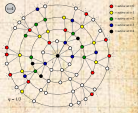
Expected size of spread

Iterative map for θ_t is key:

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

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

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



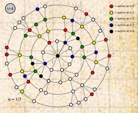
Expected size of spread:

- 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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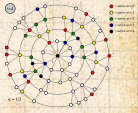

Expected size of spread:

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

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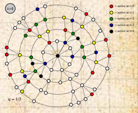

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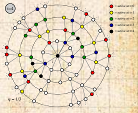


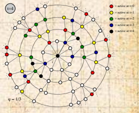
Expected size of spread:

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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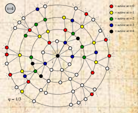

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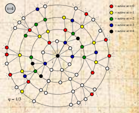

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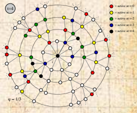

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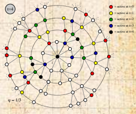

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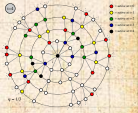
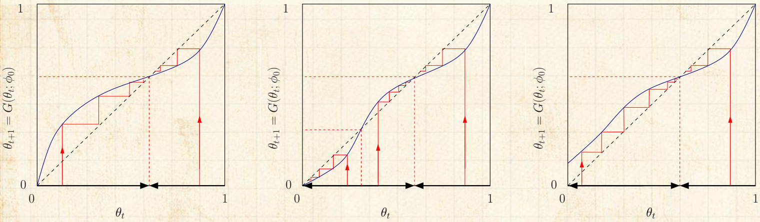
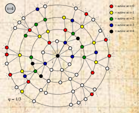


General fixed point story:



- 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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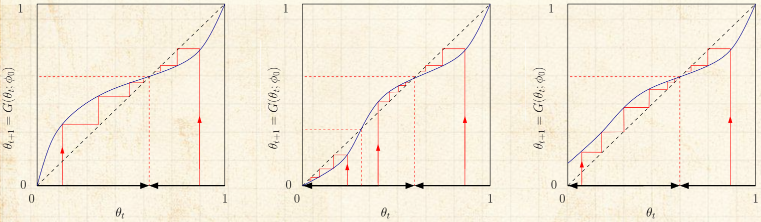

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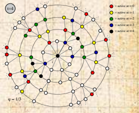

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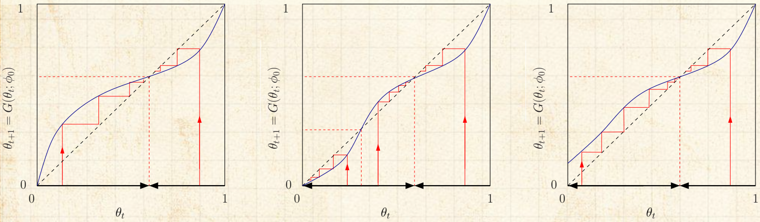

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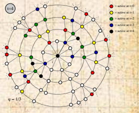

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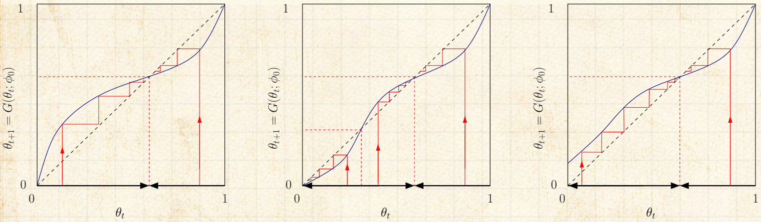

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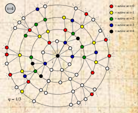
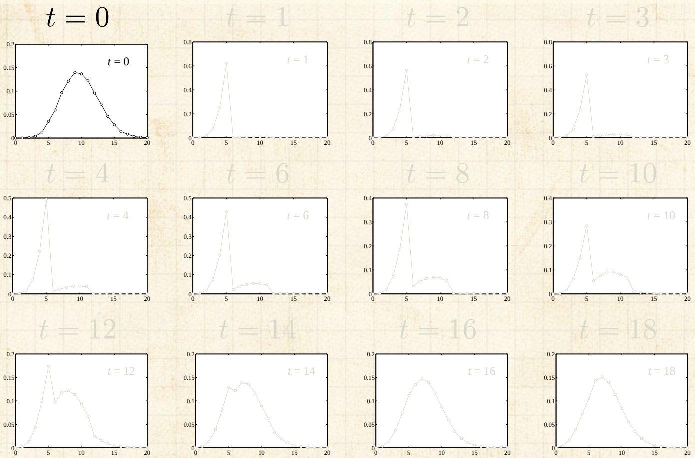
Outline

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

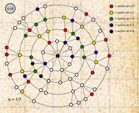
References



Early adopters—degree distributions



$P_{k,t}$ versus k



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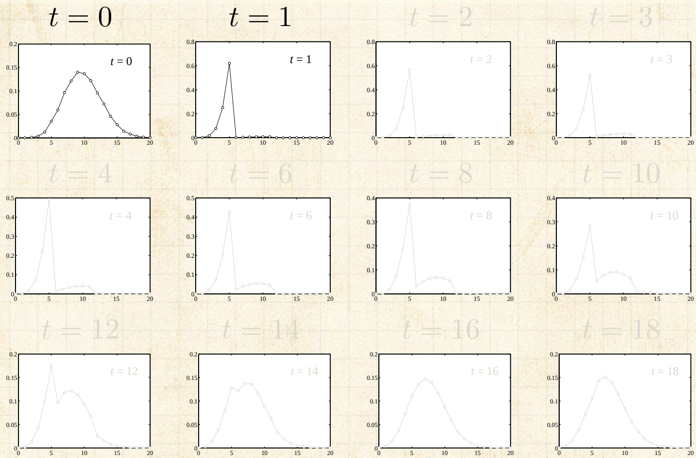

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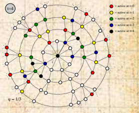

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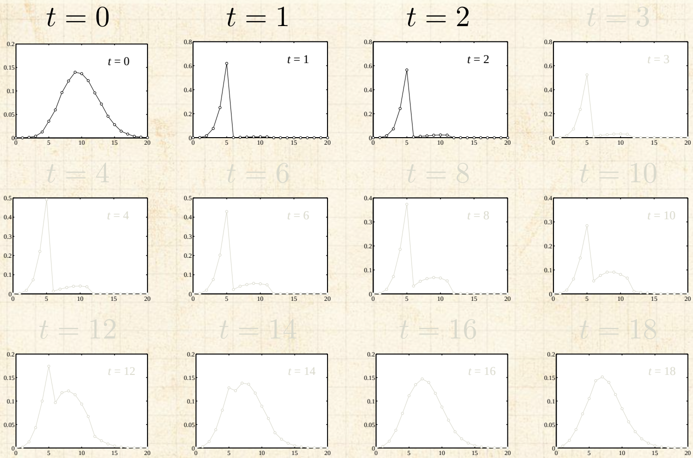

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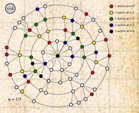

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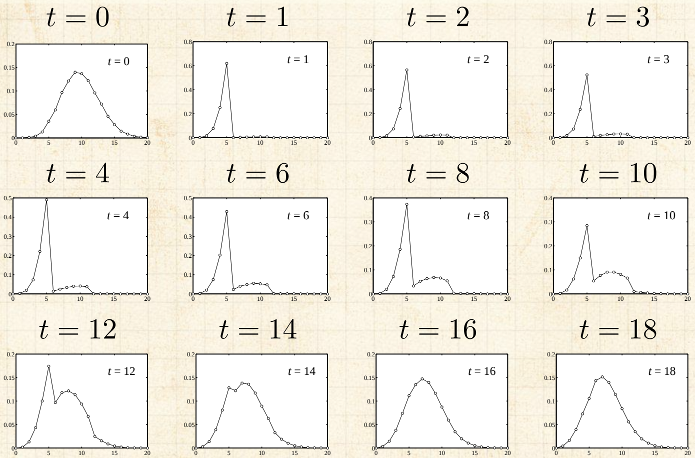

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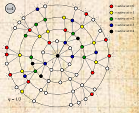
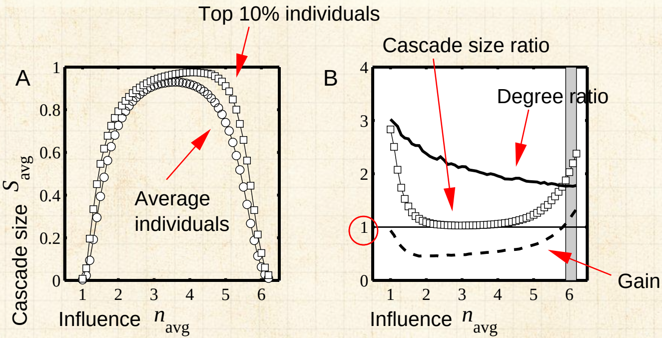
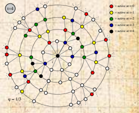


The multiplier effect:



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



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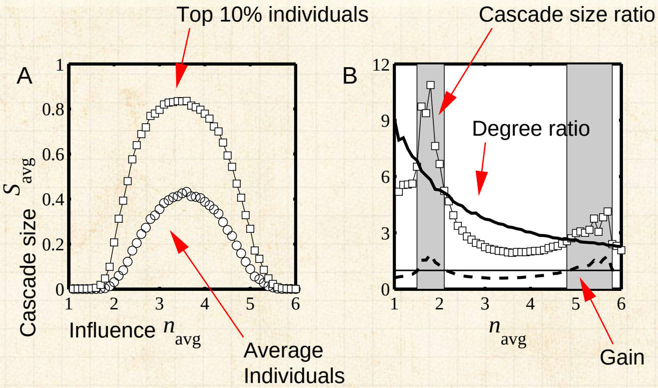
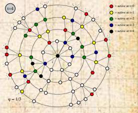
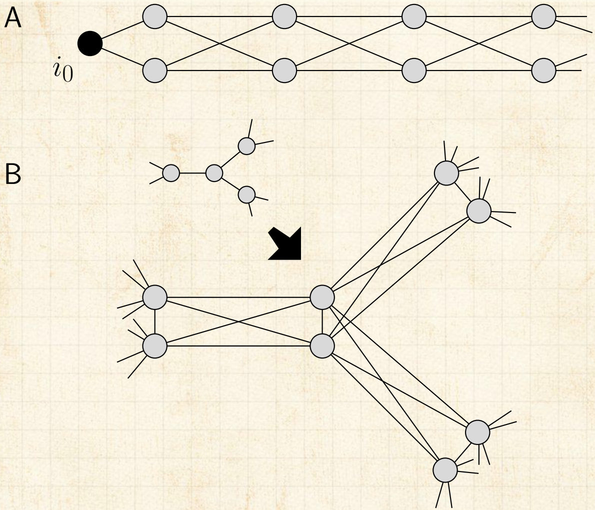


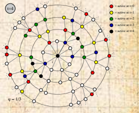
- Skewed influence distribution example.



Special subnetworks can act as triggers



$\phi = 1/3$ for all nodes



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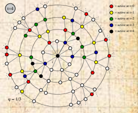
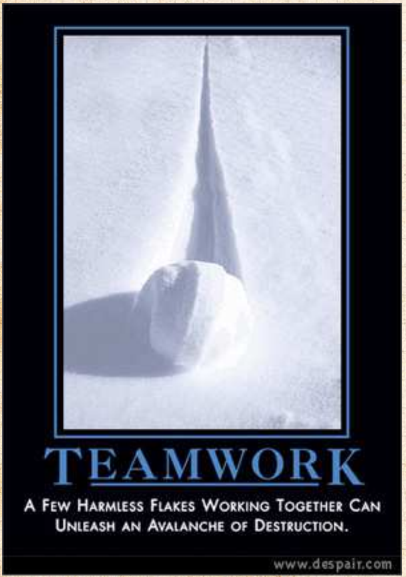
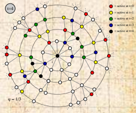


The power of groups...

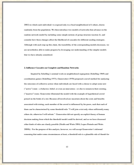


despair.com

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

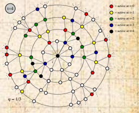


Extensions



"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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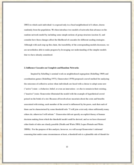

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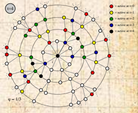

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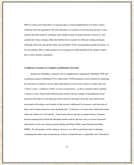

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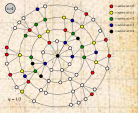

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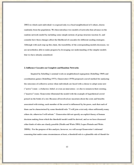

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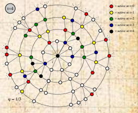
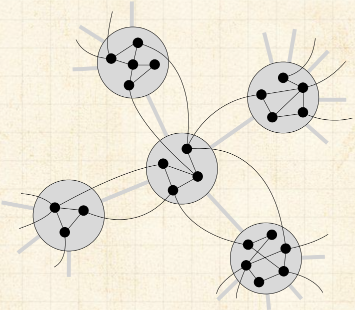
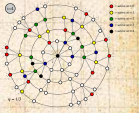


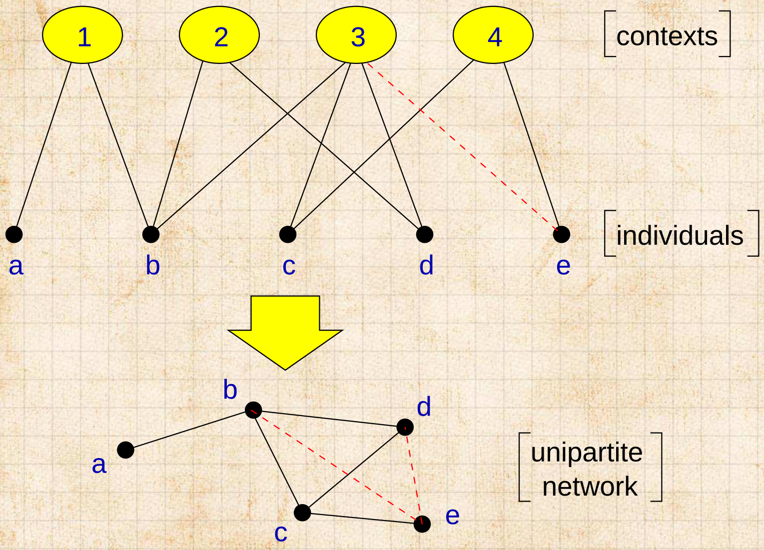
Group structure—Ramified random networks

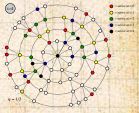


p = intergroup connection probability
q = intragroup connection probability.

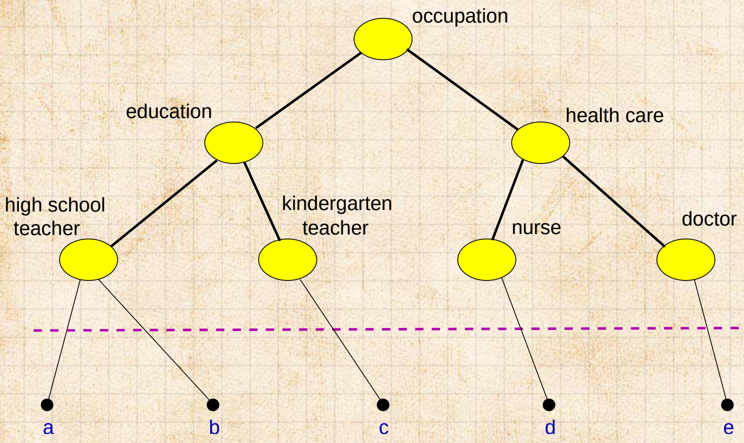


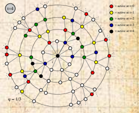
Bipartite networks



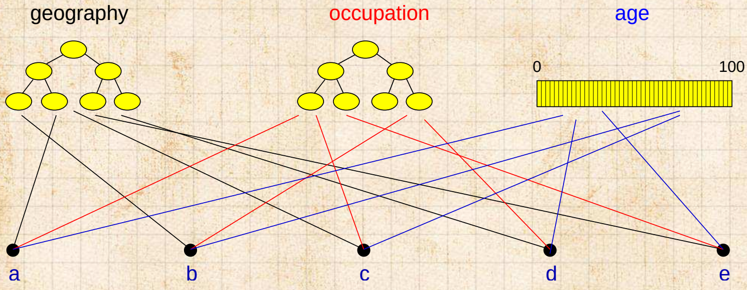


Context distance

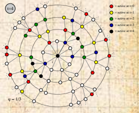




Generalized affiliation model

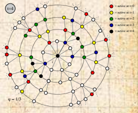


(Blau & Schwartz, Simmel, Breiger)



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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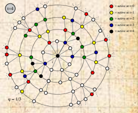
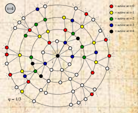
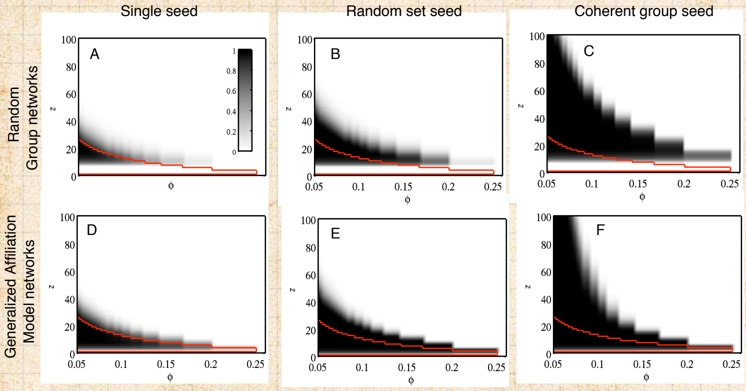


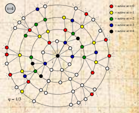
Generalized affiliation model networks with triadic closure

- 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

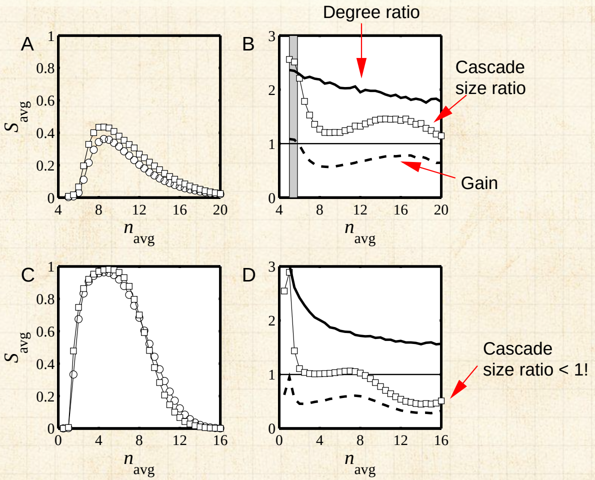


Cascade windows for group-based networks

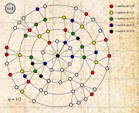




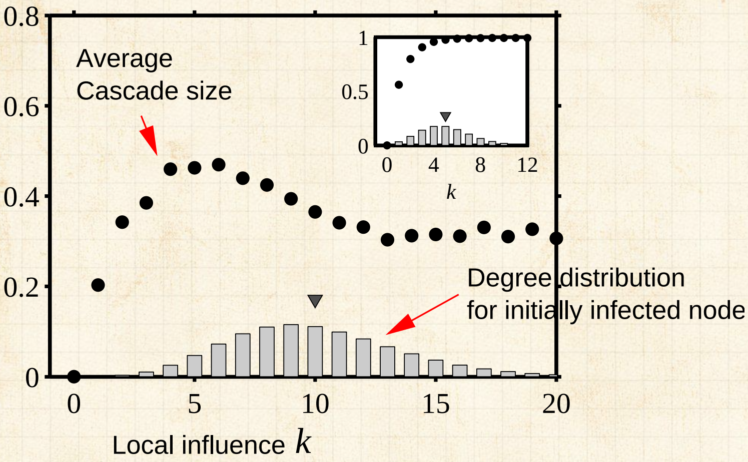
Multiplier effect for group-based networks:



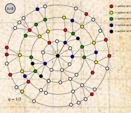
- Multiplier almost always below 1.



Assortativity in group-based networks



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



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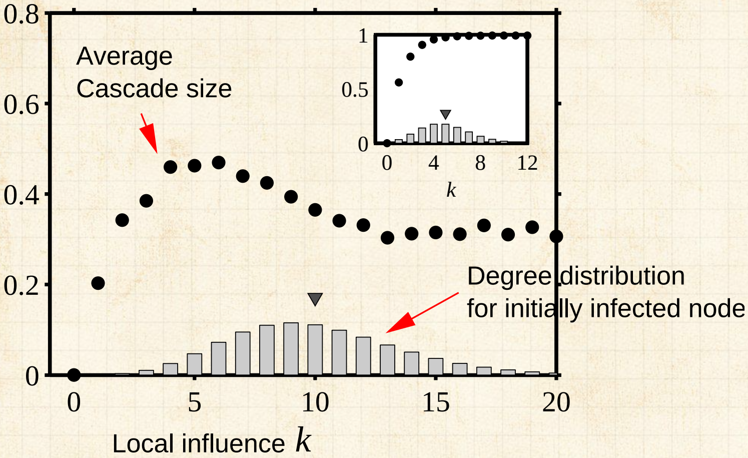

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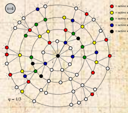
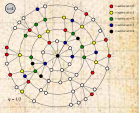


Social contagion

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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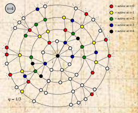

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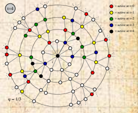

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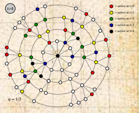

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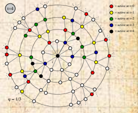

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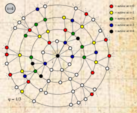

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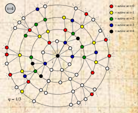

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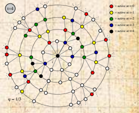
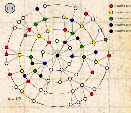


Social contagion

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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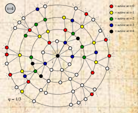

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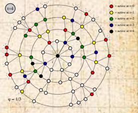

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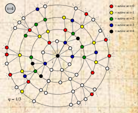

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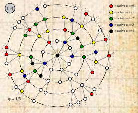

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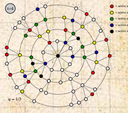
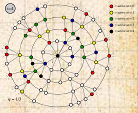


Spreading and unspreading: Empires



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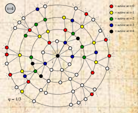

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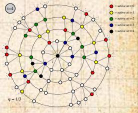

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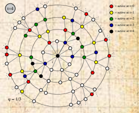

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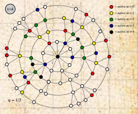

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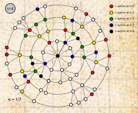

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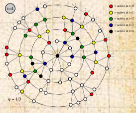

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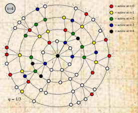

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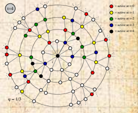

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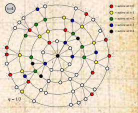

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