Social Contagion

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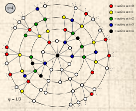
Principles of Complex Systems, Vol. 1 | @pocsvox
CSYS/MATH 300, Fall, 2020

Prof. Peter Sheridan Dodds | @peterdodds

Computational Story Lab | Vermont Complex Systems Center
Vermont Advanced Computing Core | University of Vermont



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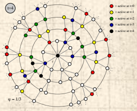

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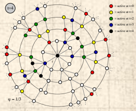
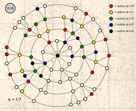
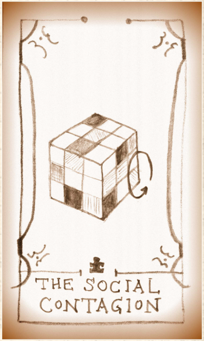
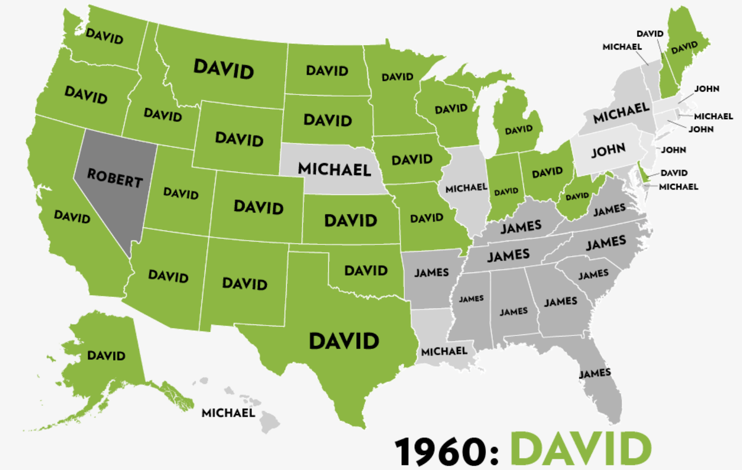


Outline




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


THE SOCIAL CONTAGION



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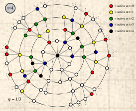

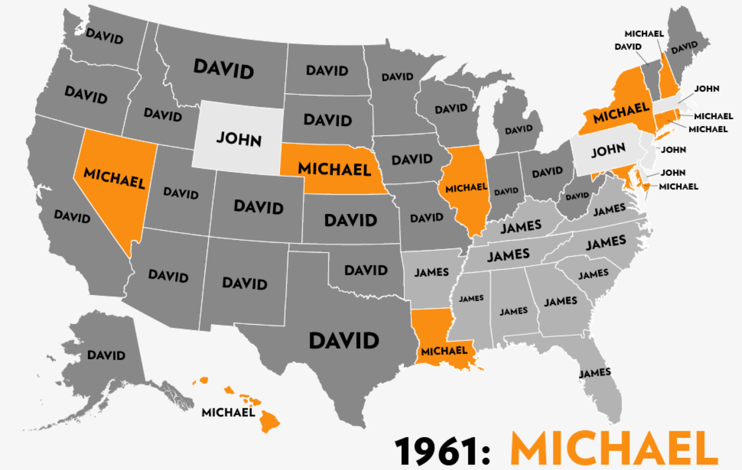

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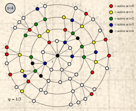

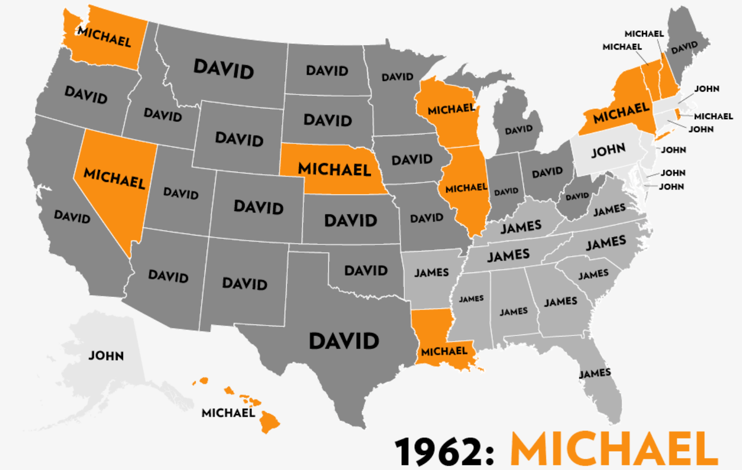

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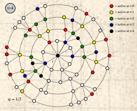

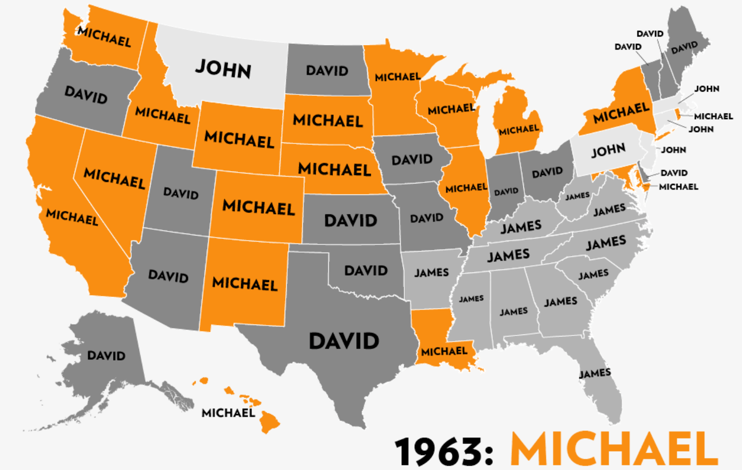

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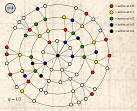

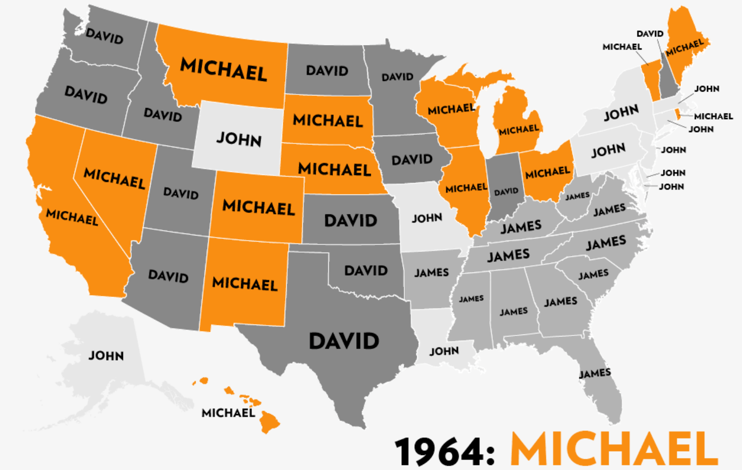

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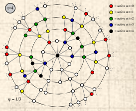

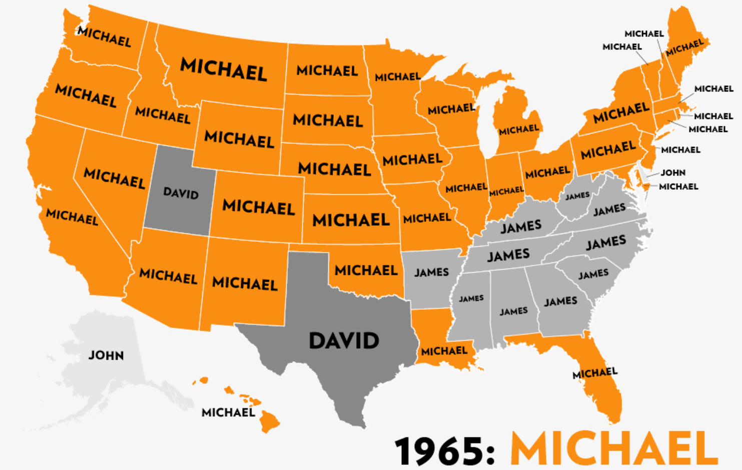

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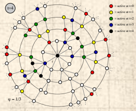

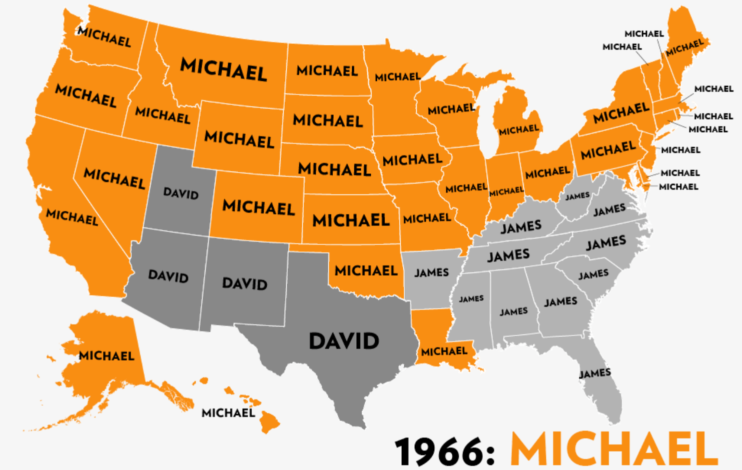

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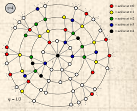

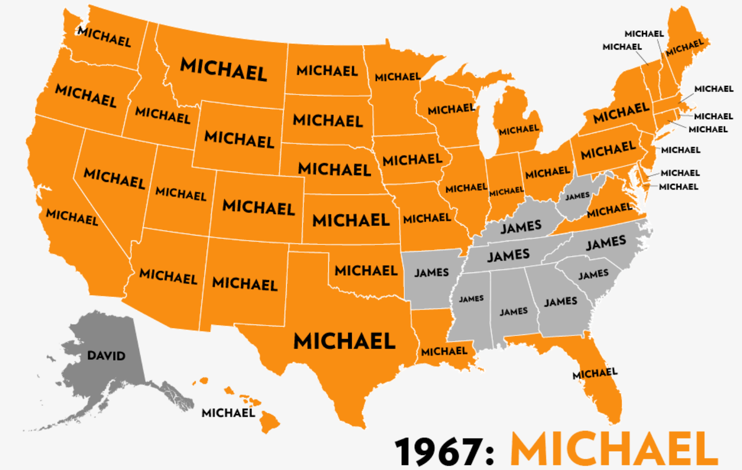

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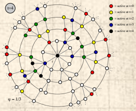

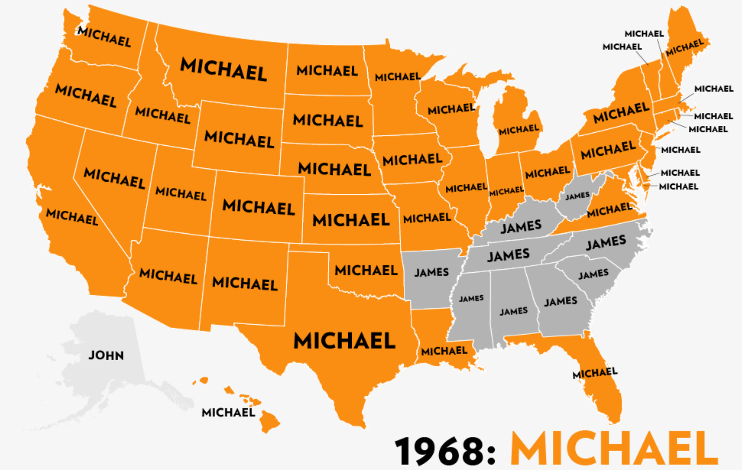

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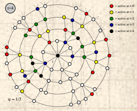

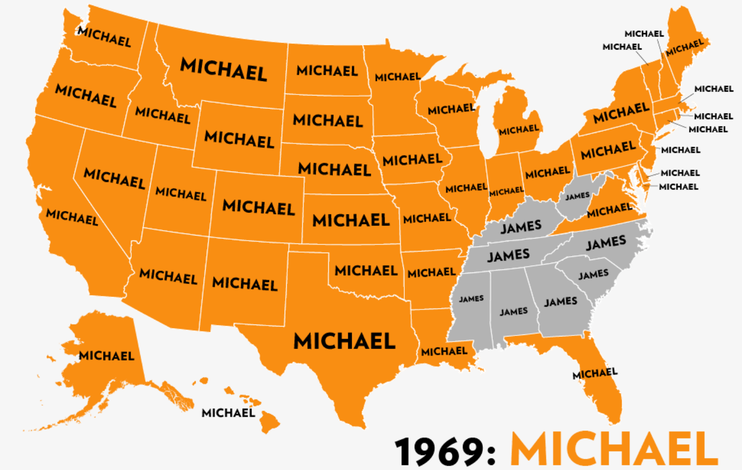

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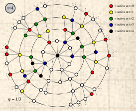

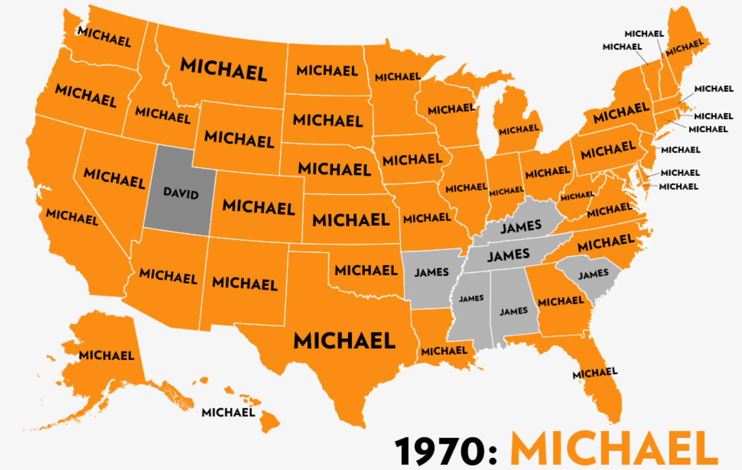

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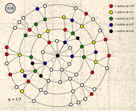

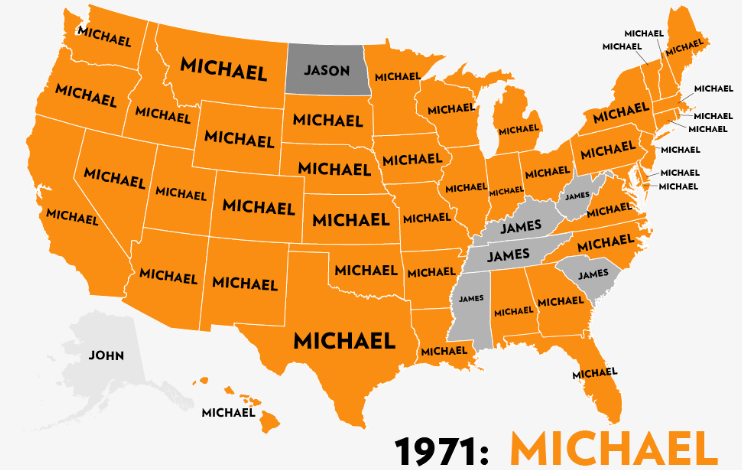

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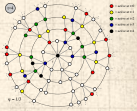

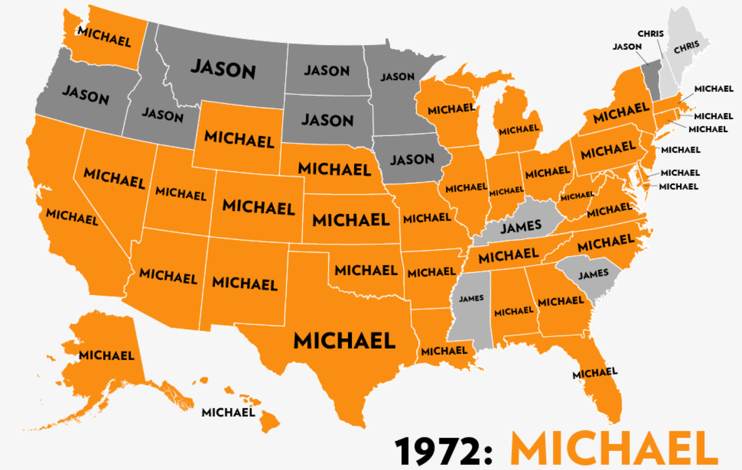

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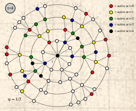

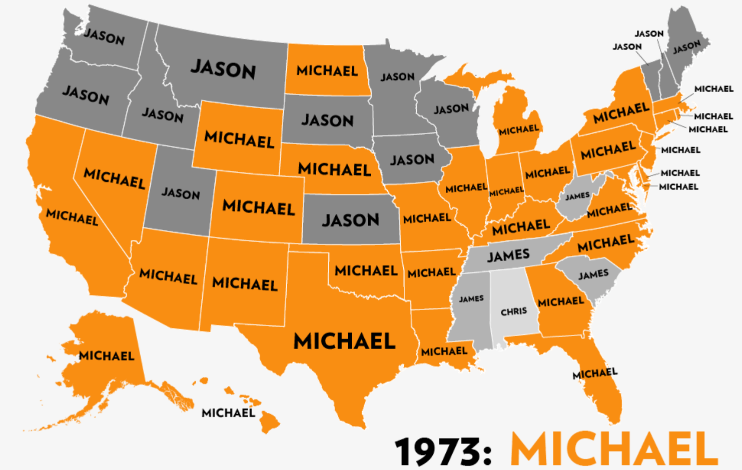

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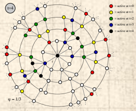

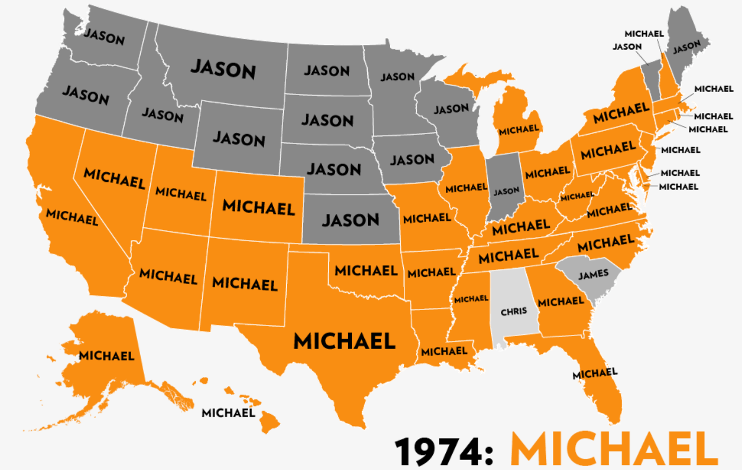

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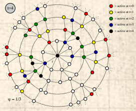

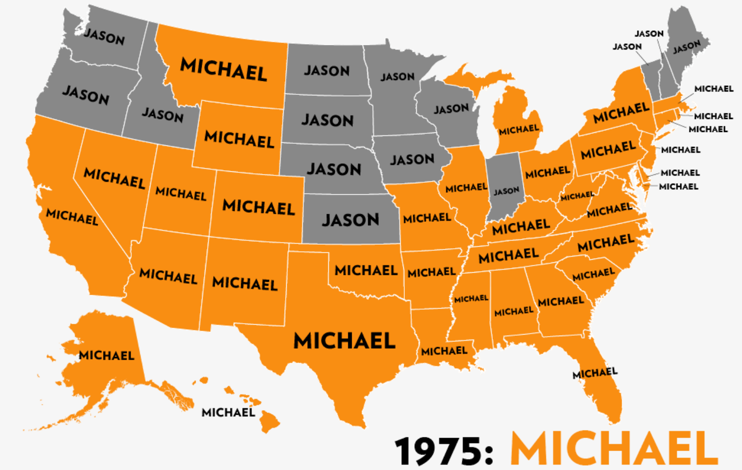

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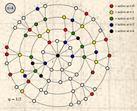

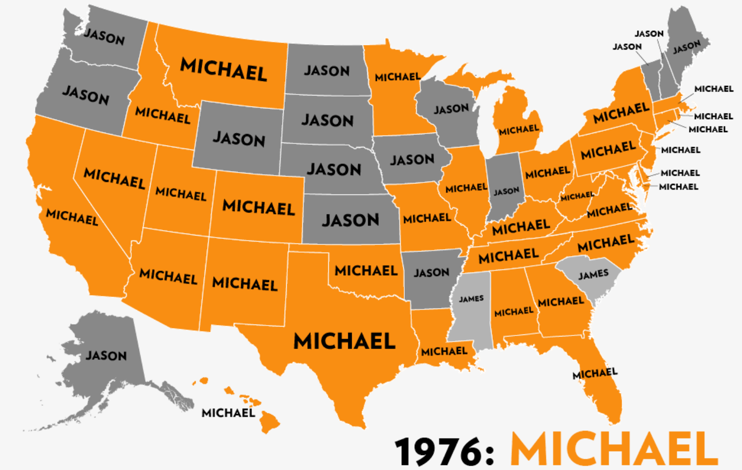

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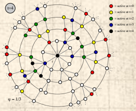

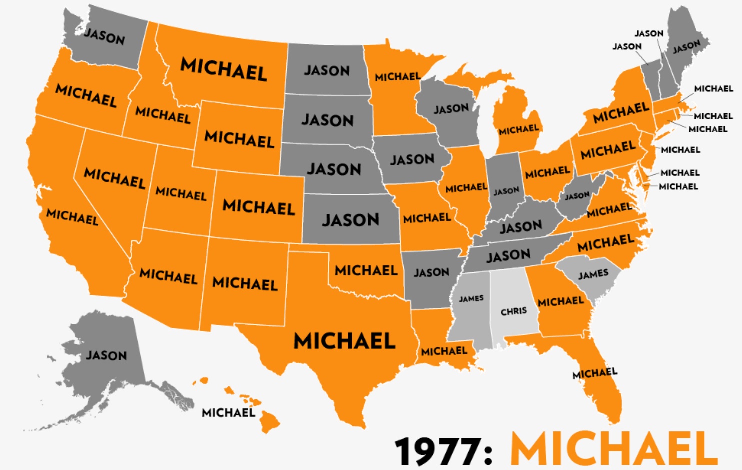

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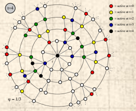

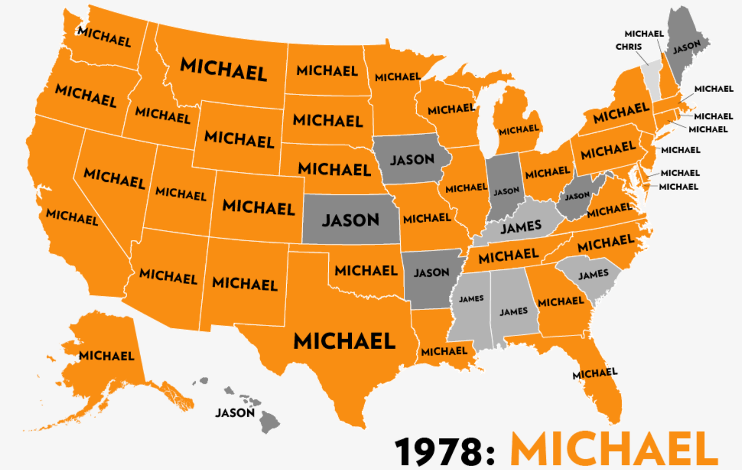

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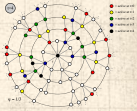

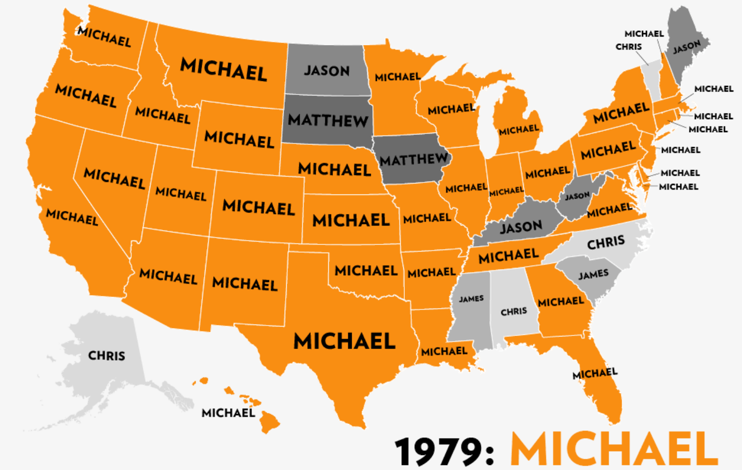

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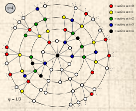

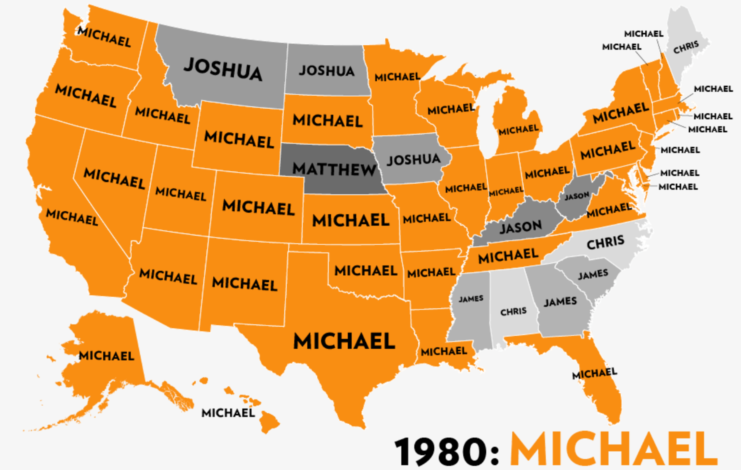

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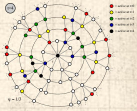

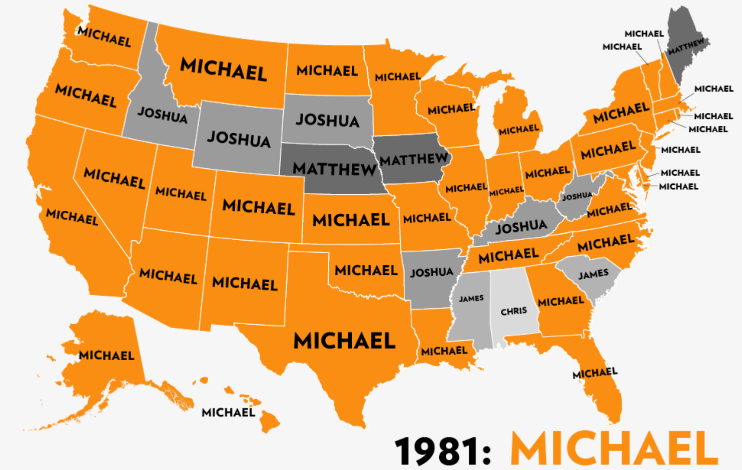

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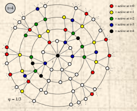

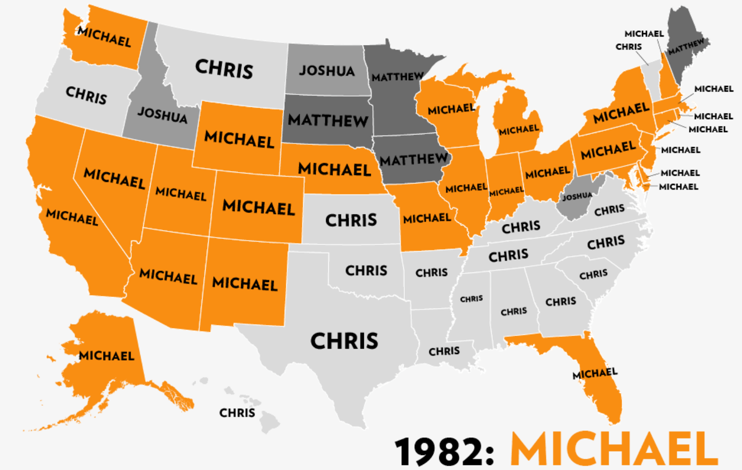

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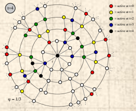

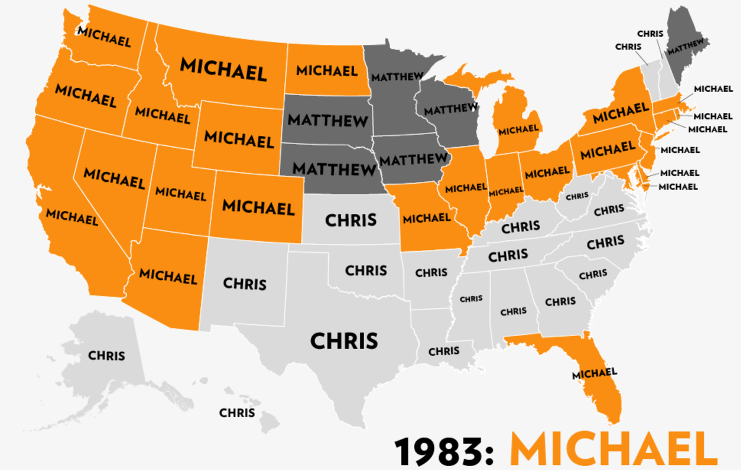

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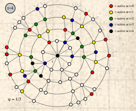

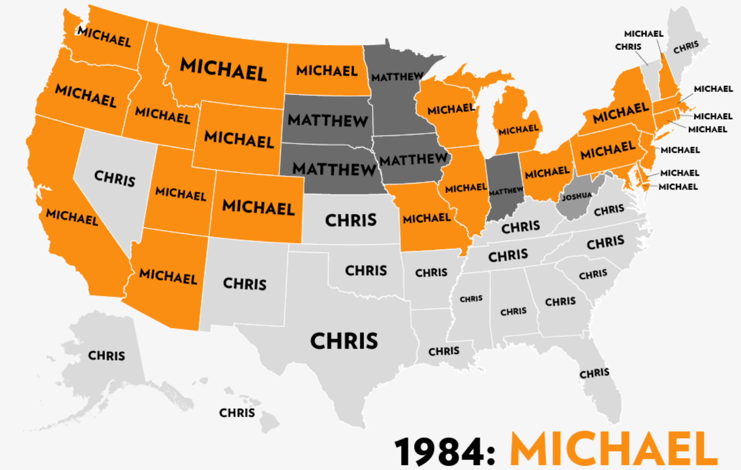

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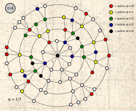

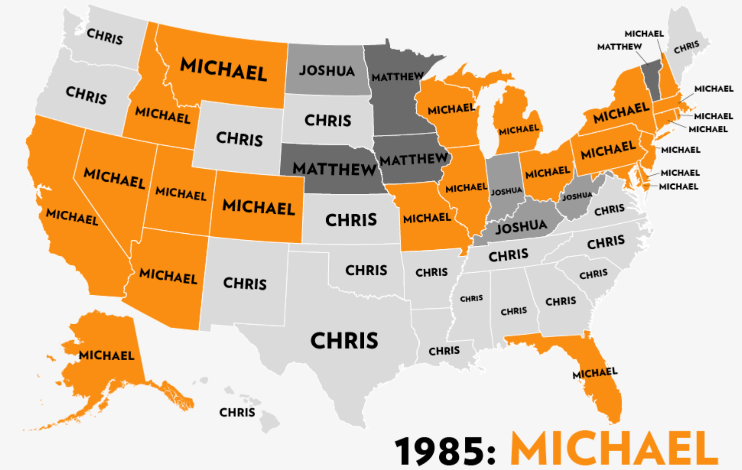

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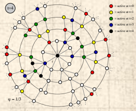

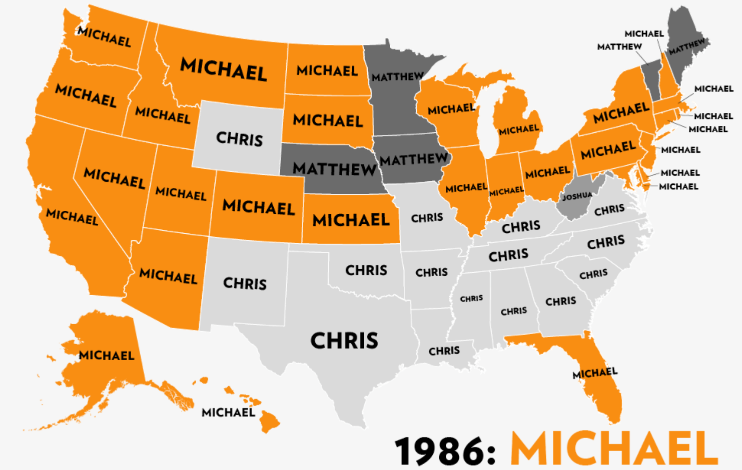

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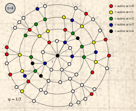

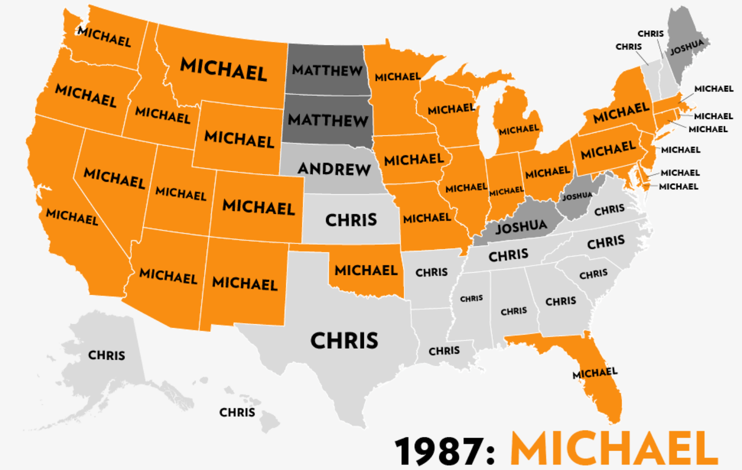

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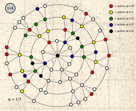

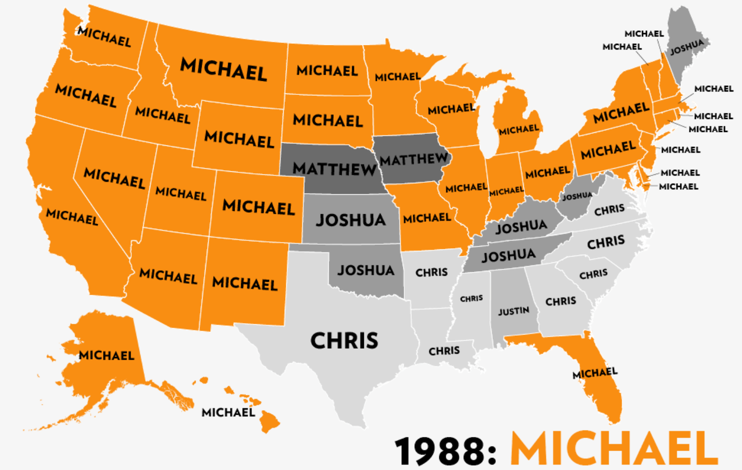

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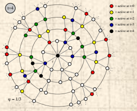

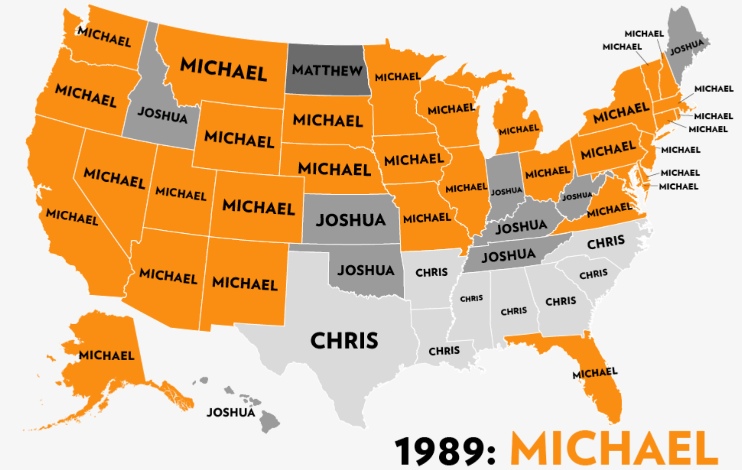

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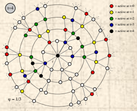

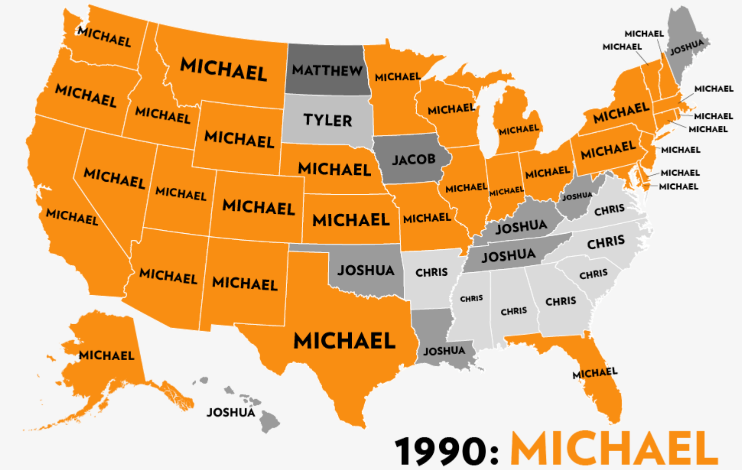

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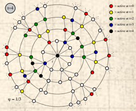

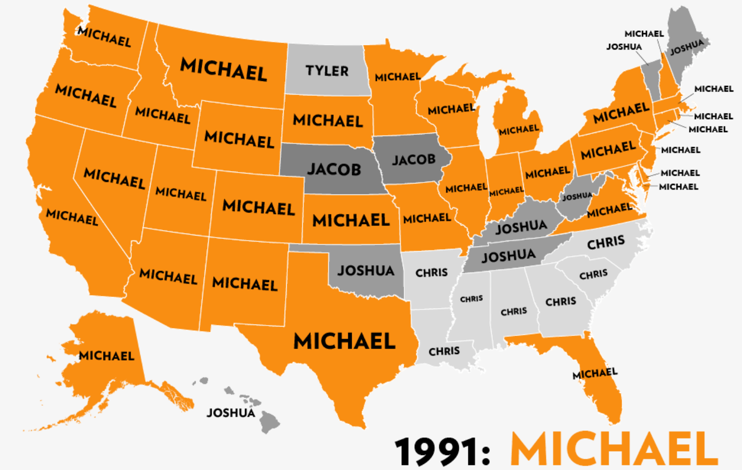

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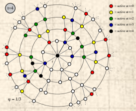

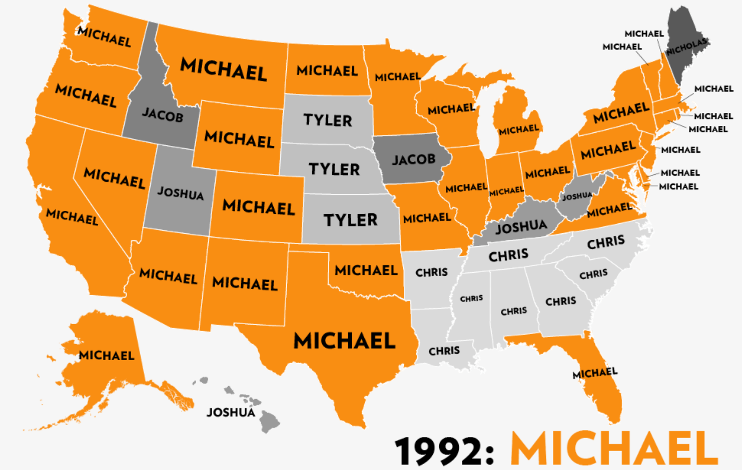

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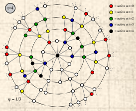

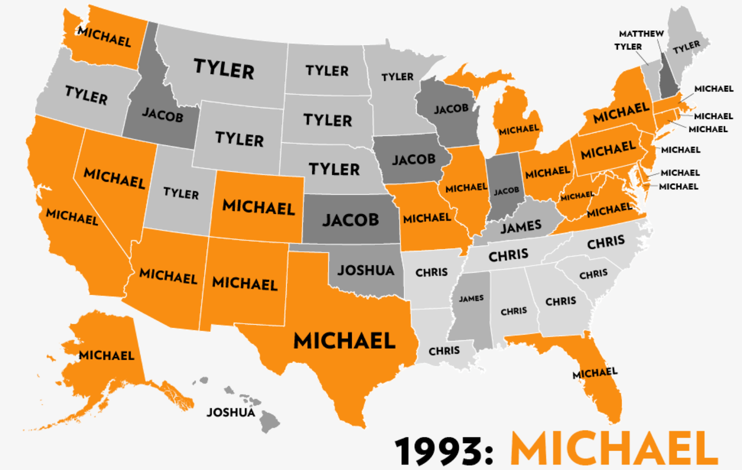

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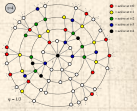

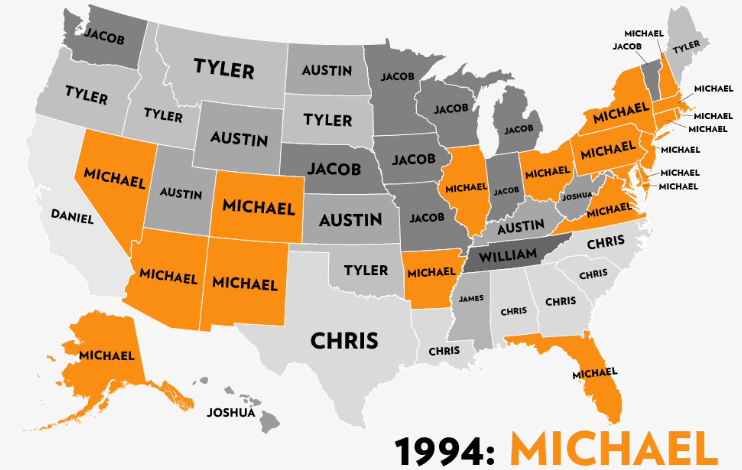

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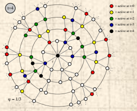

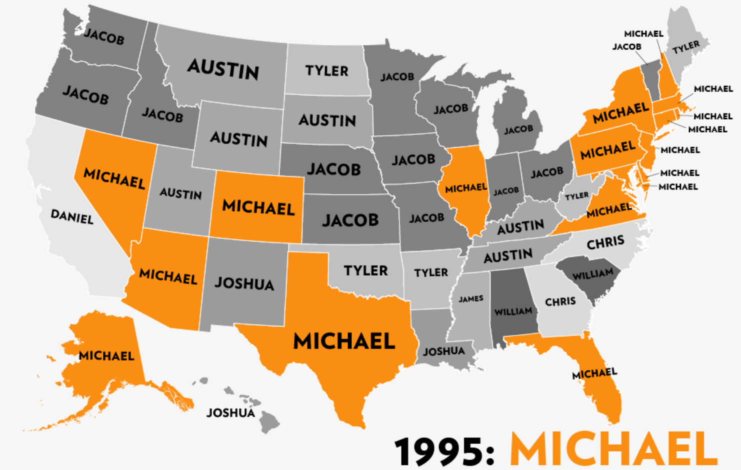

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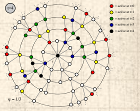

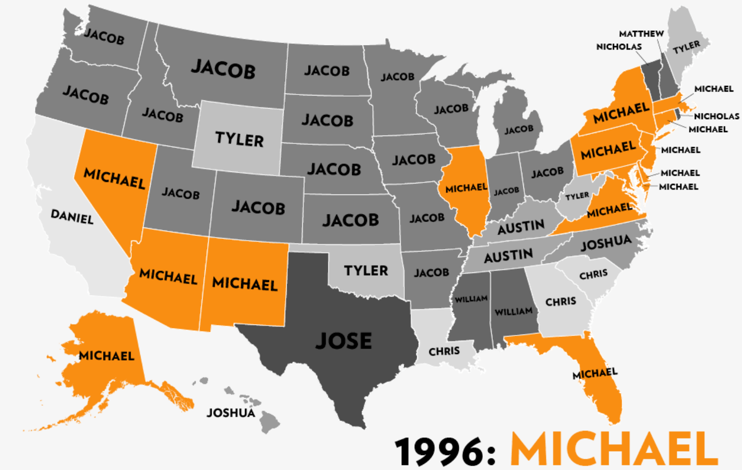

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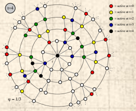

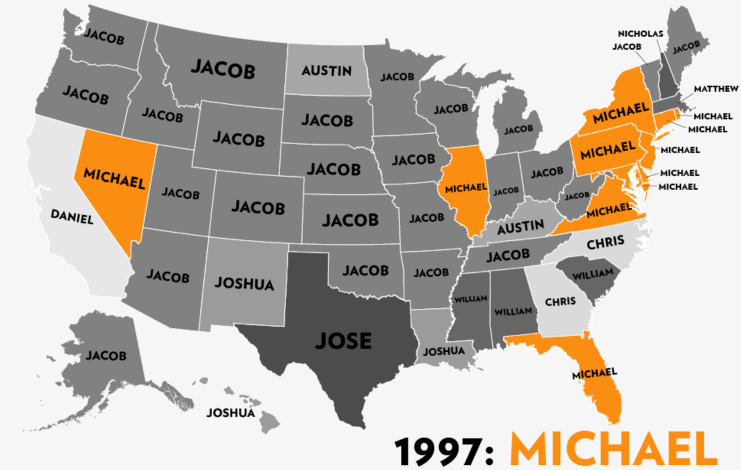

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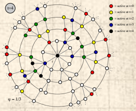

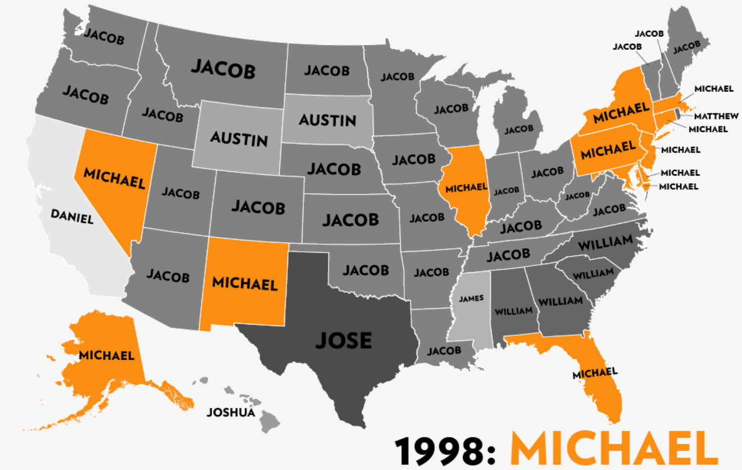

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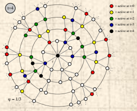

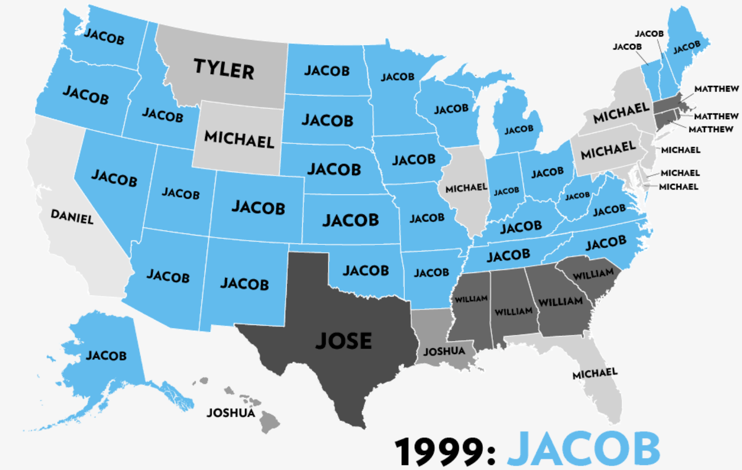

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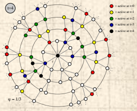

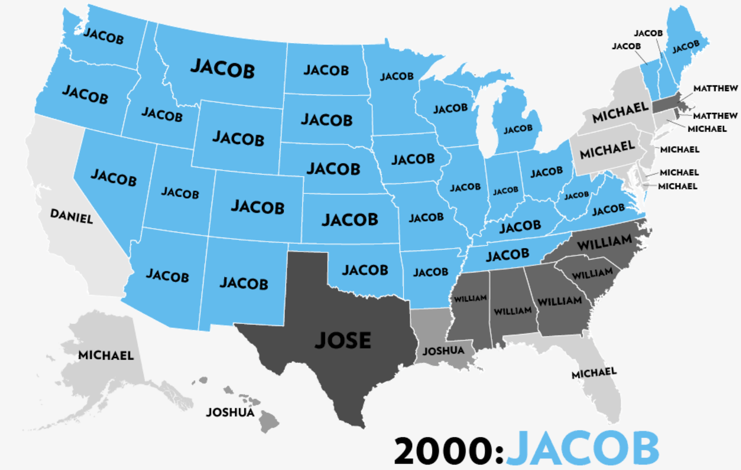

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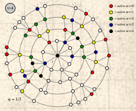

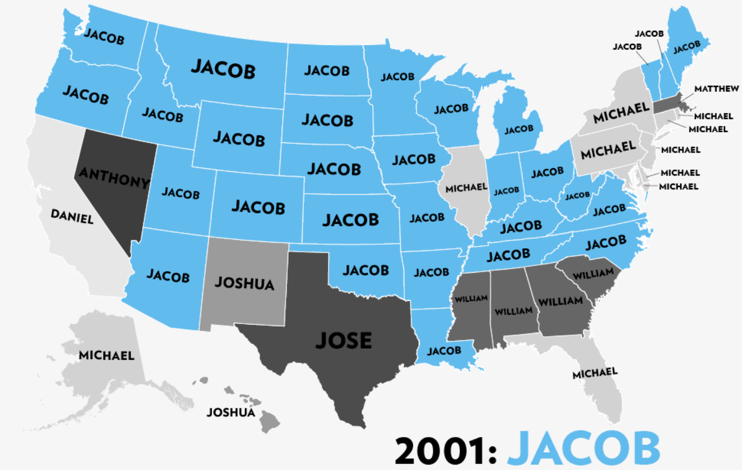

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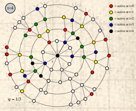

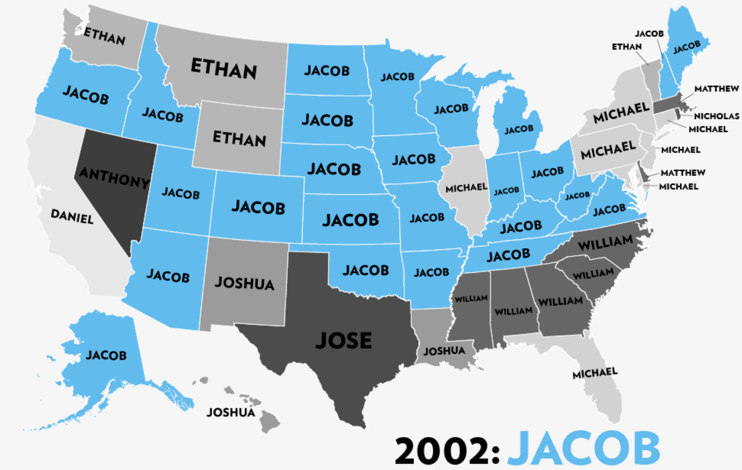

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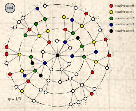

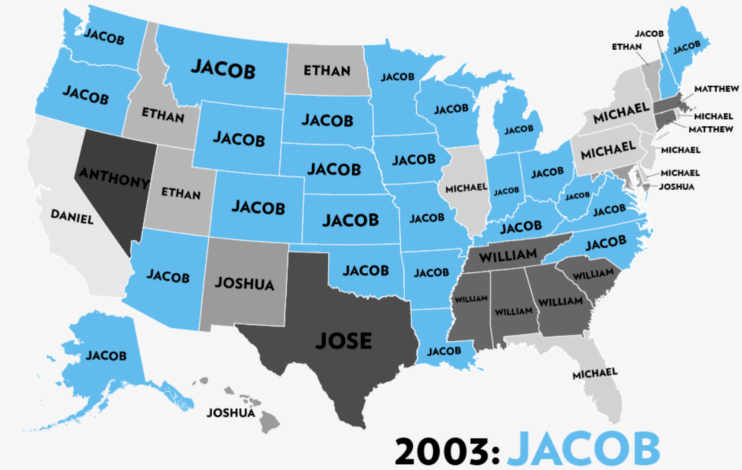

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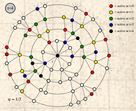

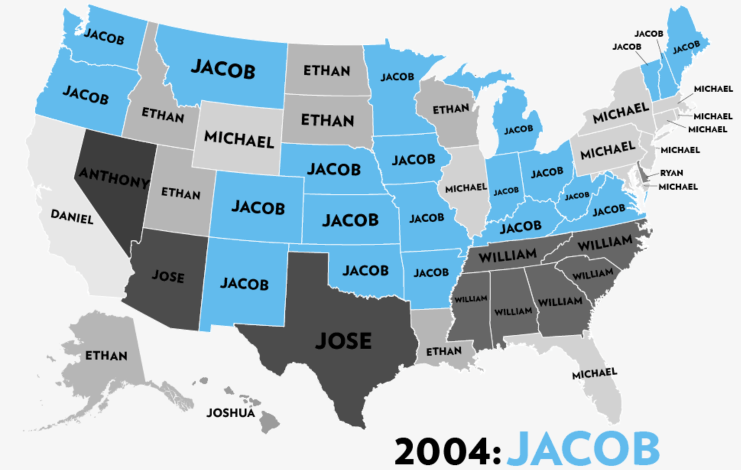

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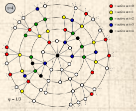

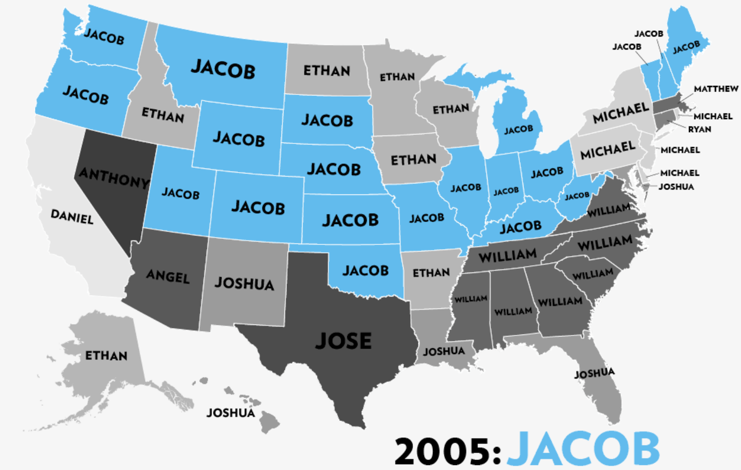

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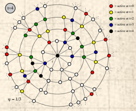

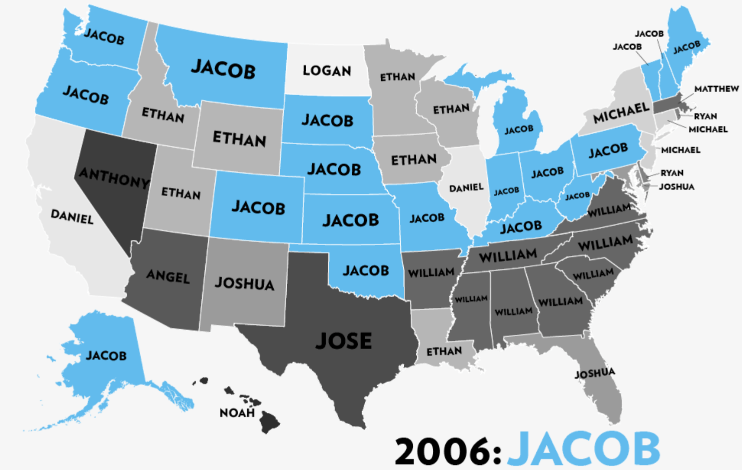

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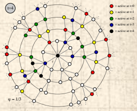

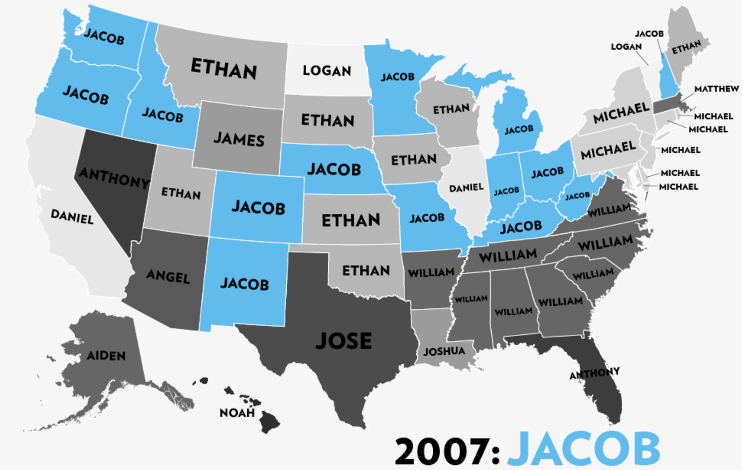

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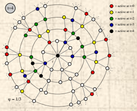

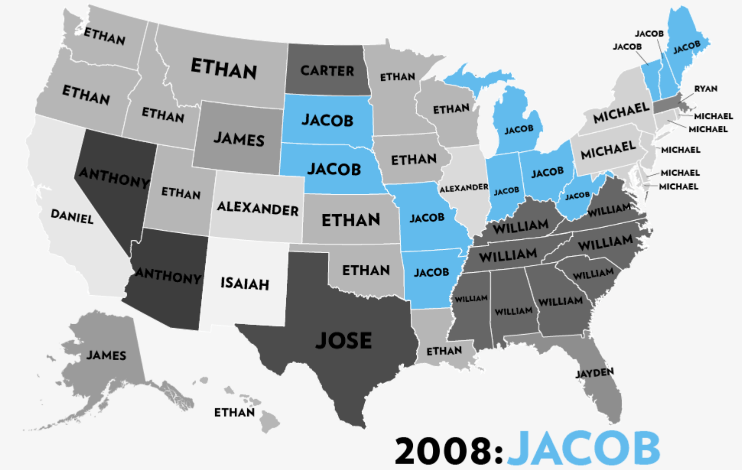

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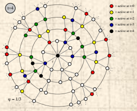

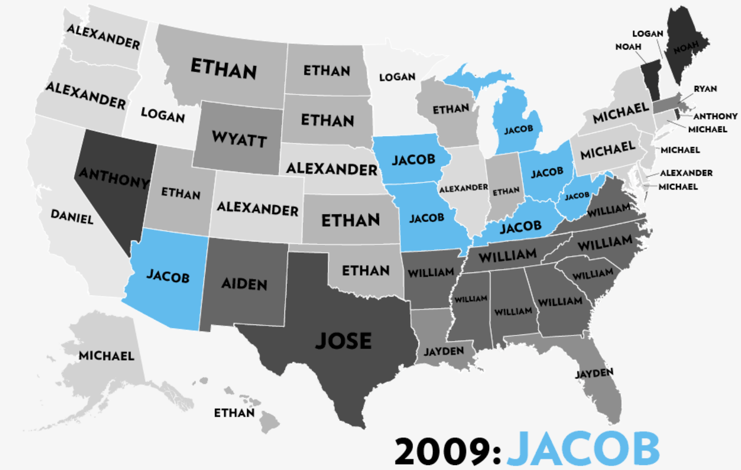

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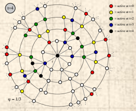

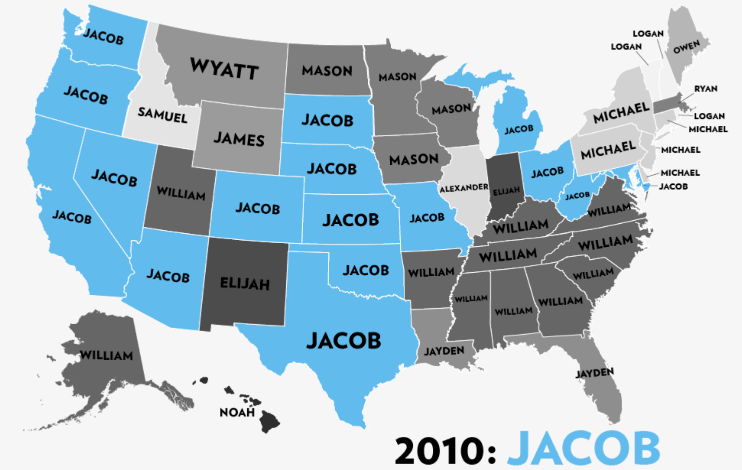

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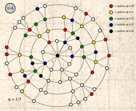

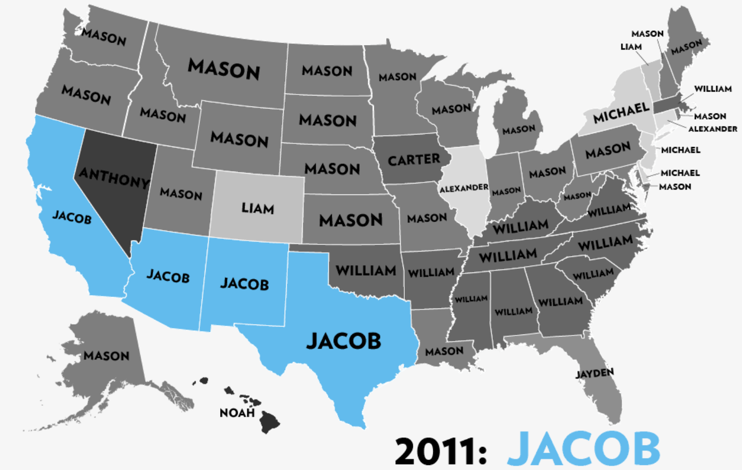

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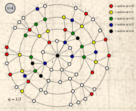

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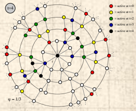

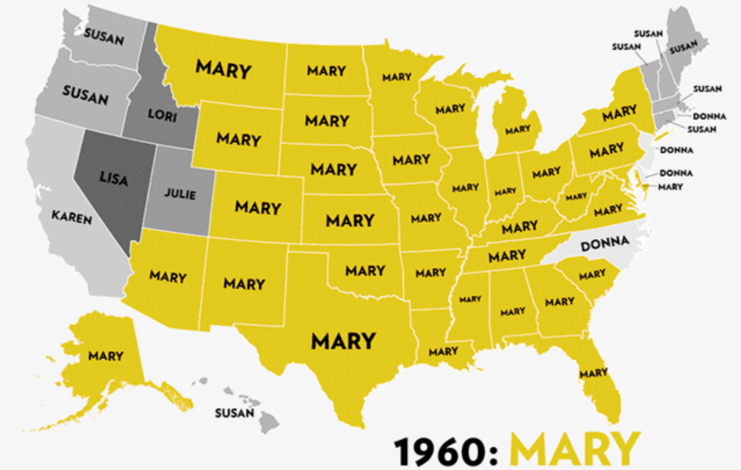

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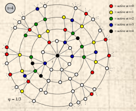

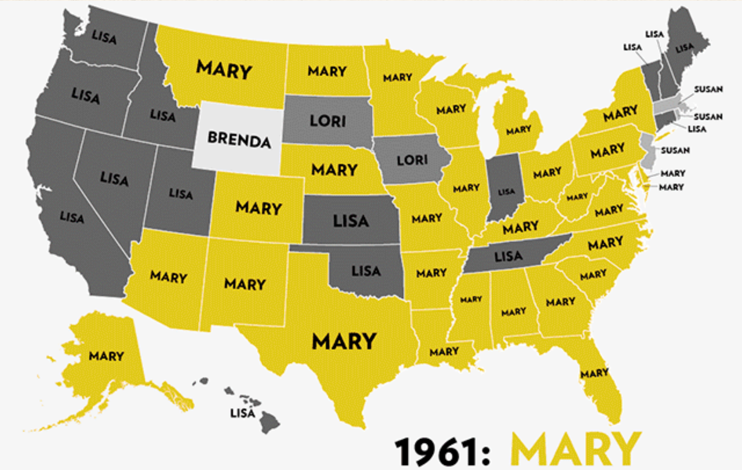

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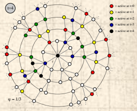

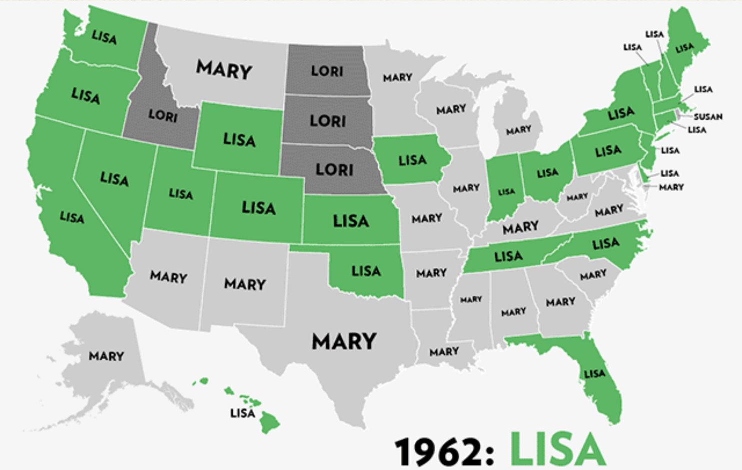

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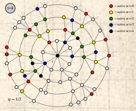

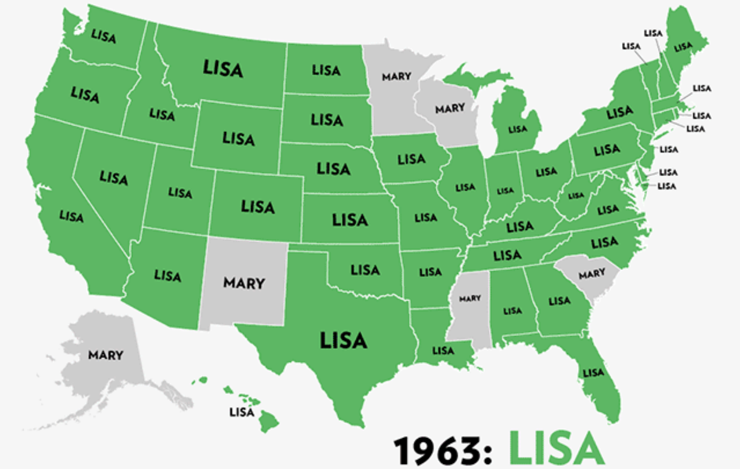

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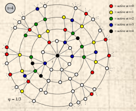

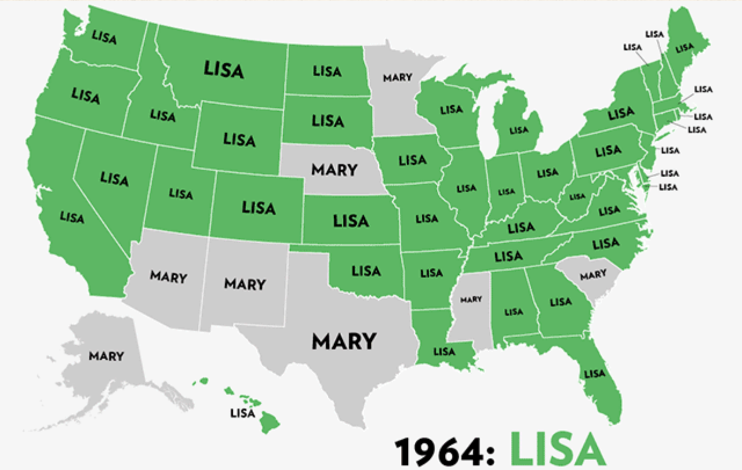

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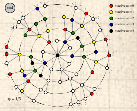

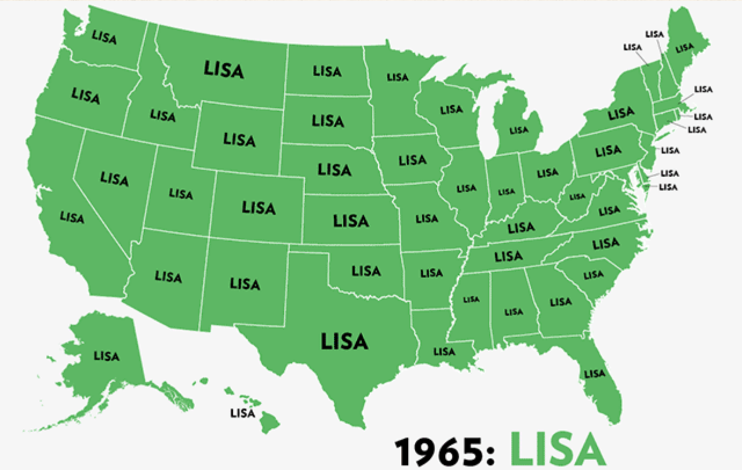

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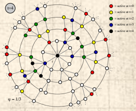

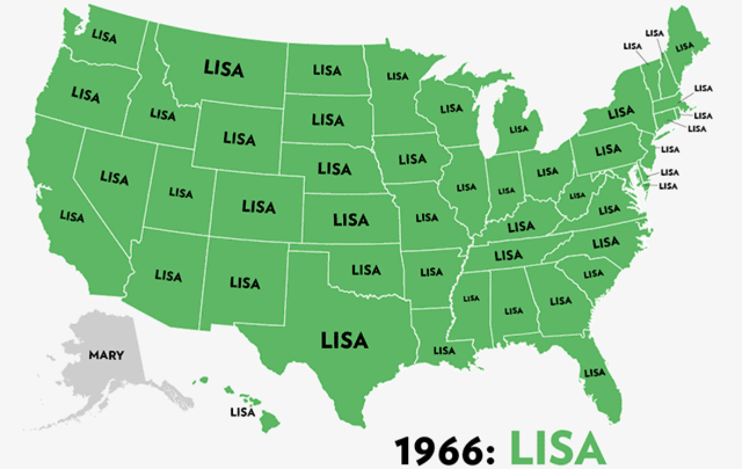

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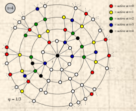

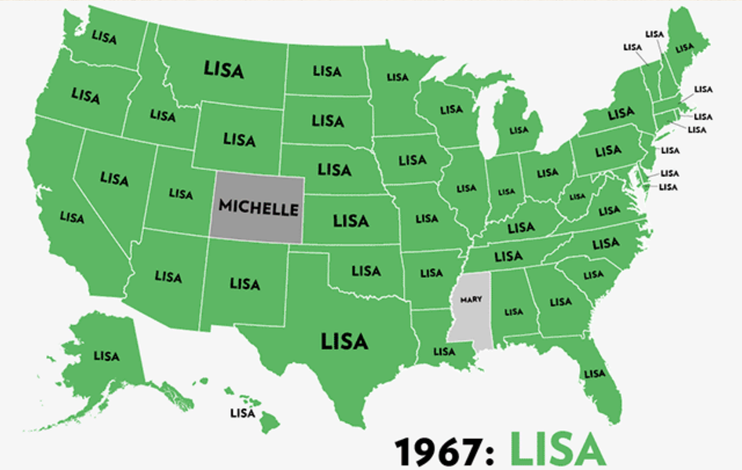

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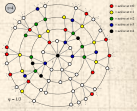

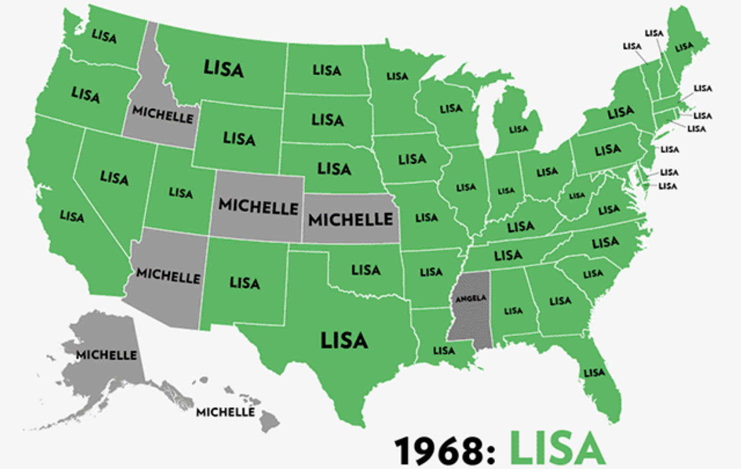

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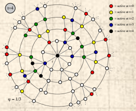

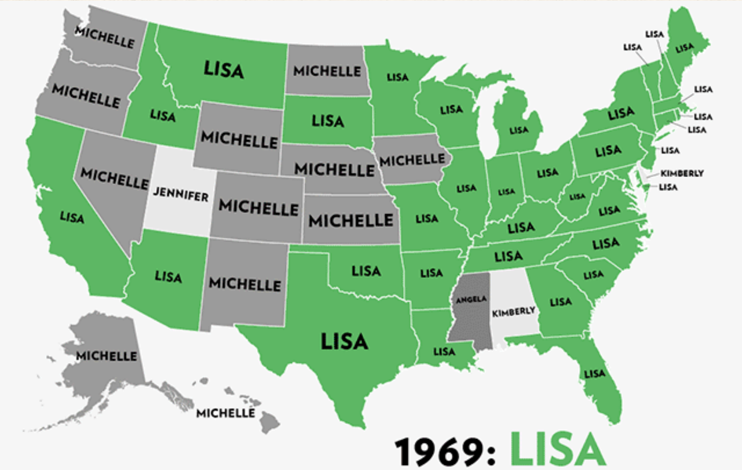

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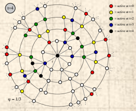

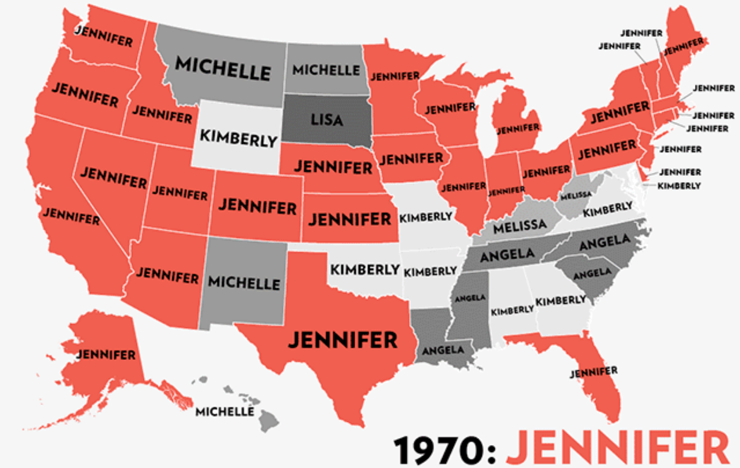

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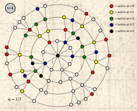

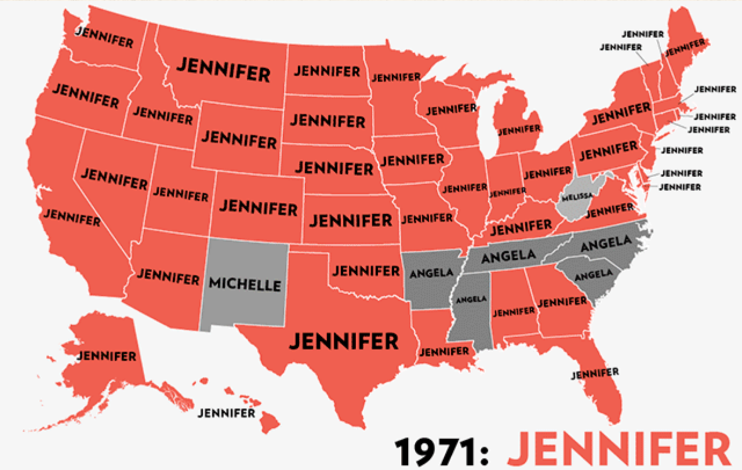

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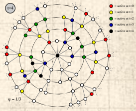

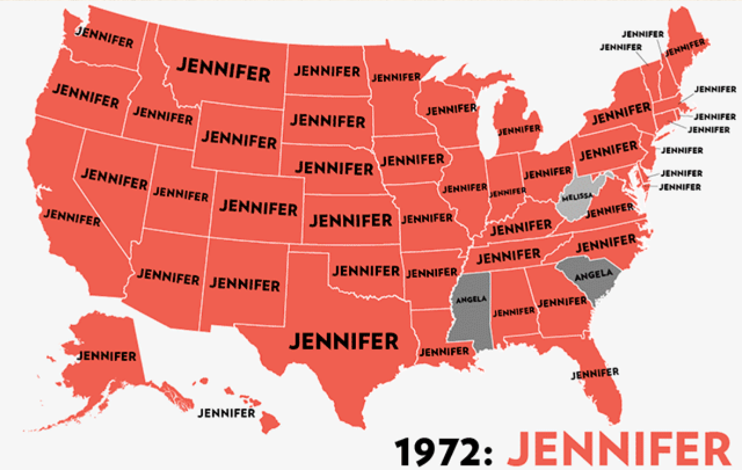

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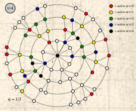

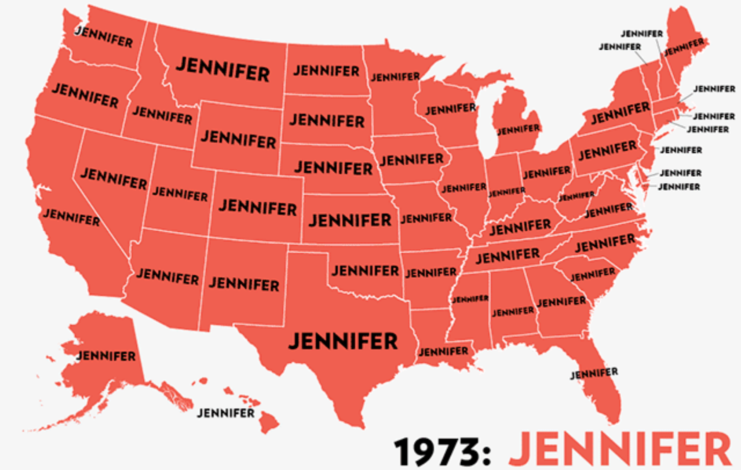

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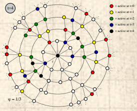

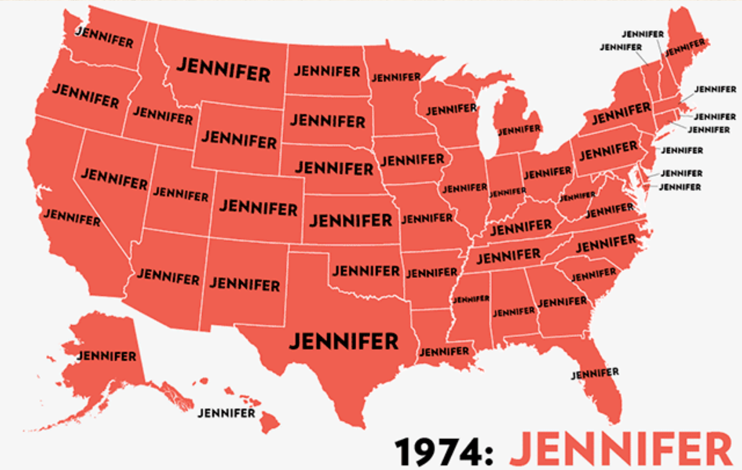

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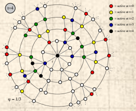

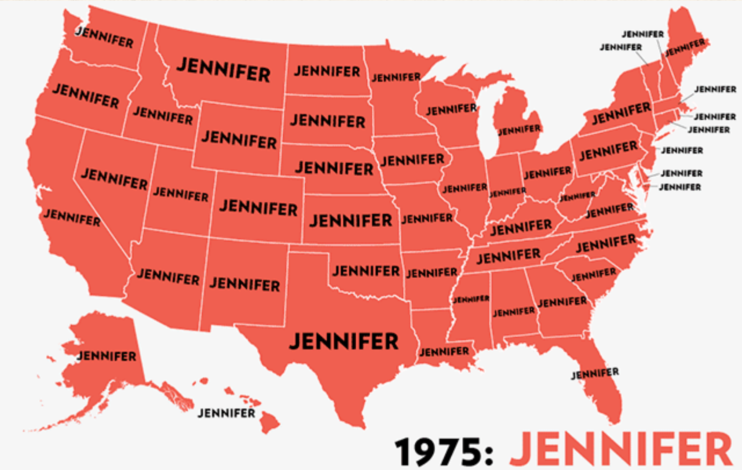

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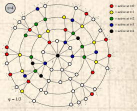

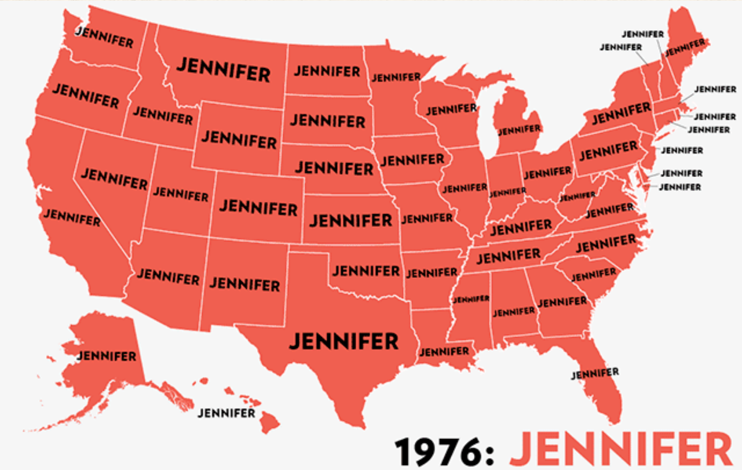

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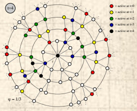

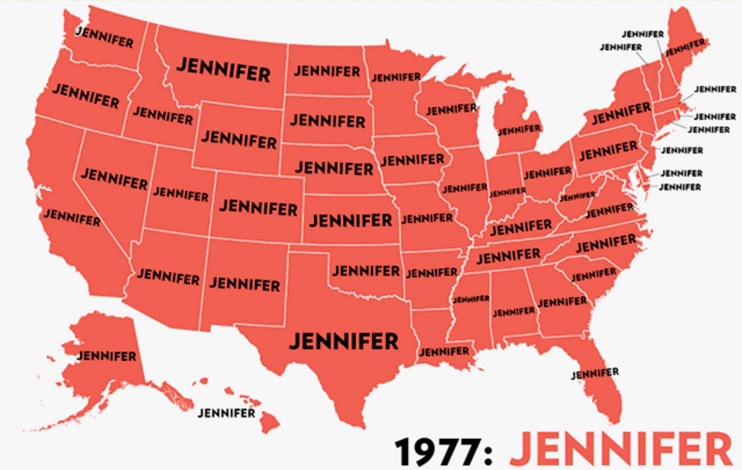

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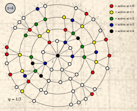

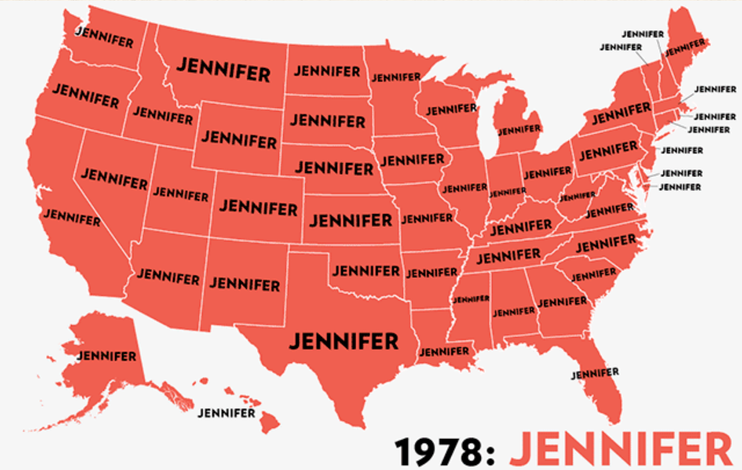

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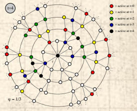

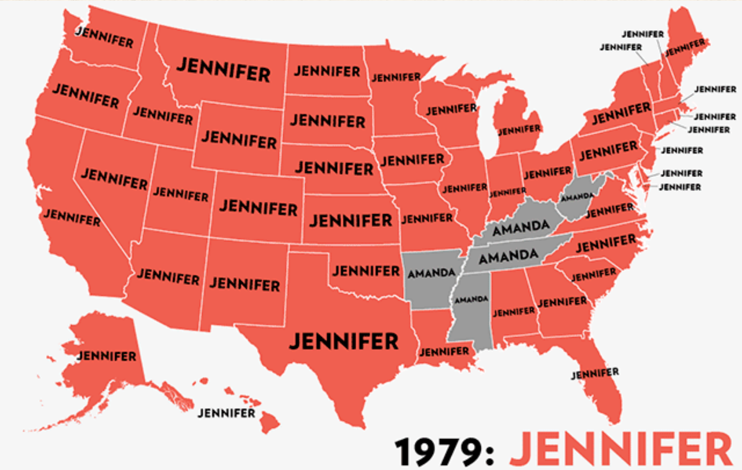

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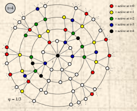

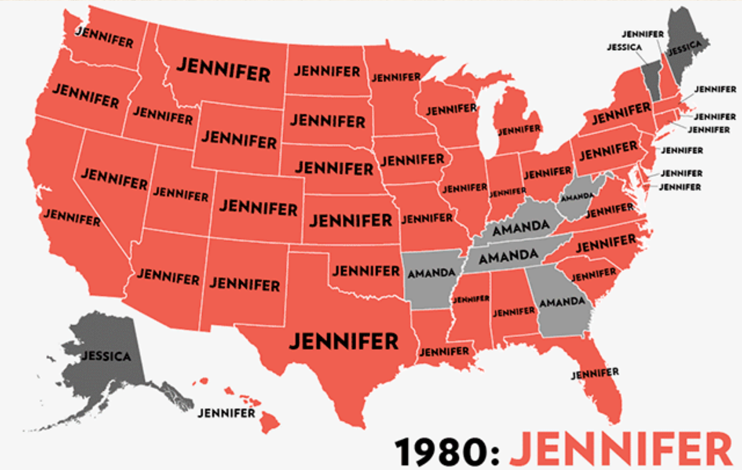

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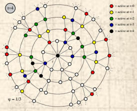

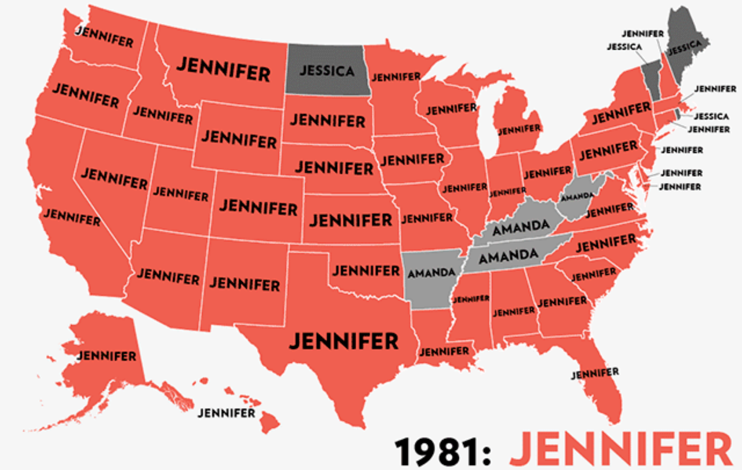

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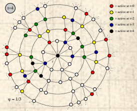

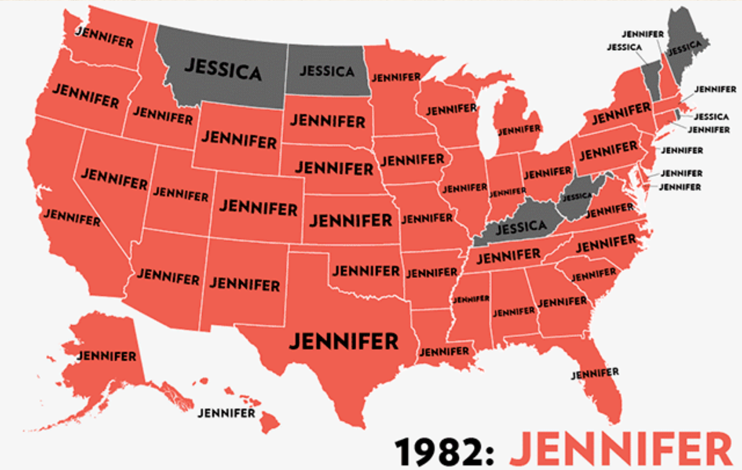

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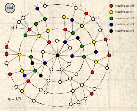

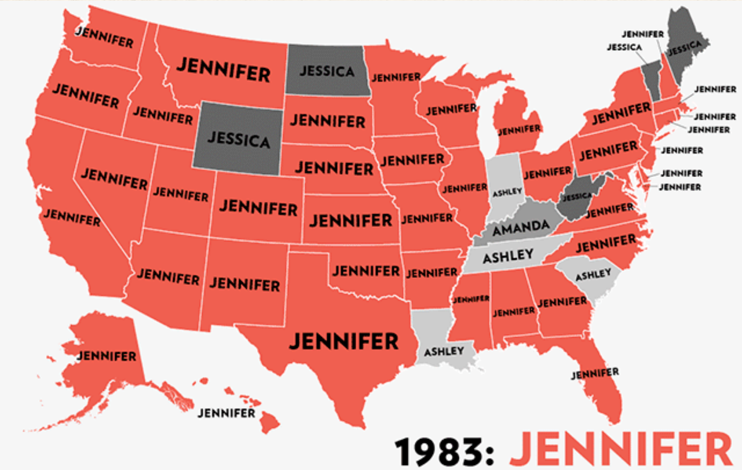

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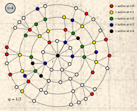

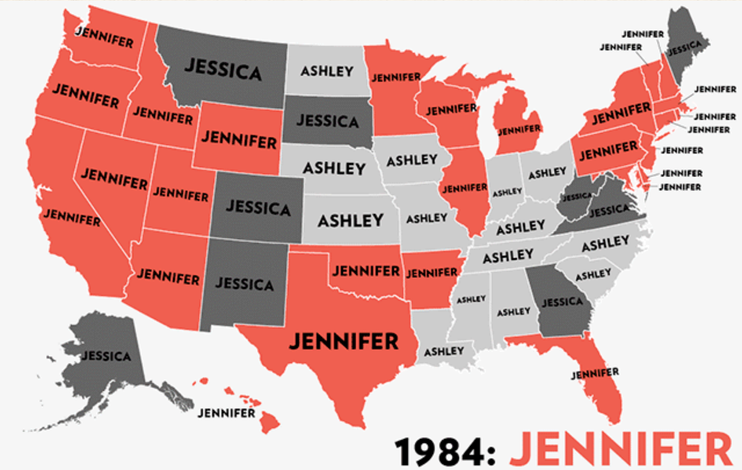

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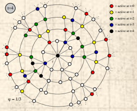

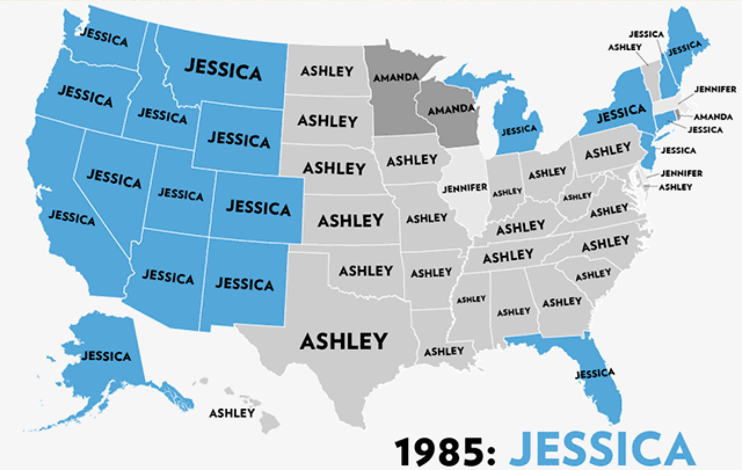

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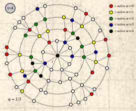

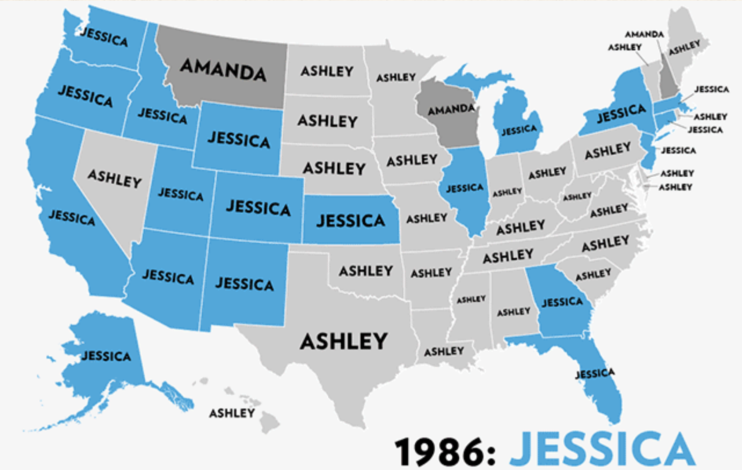

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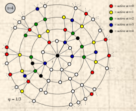

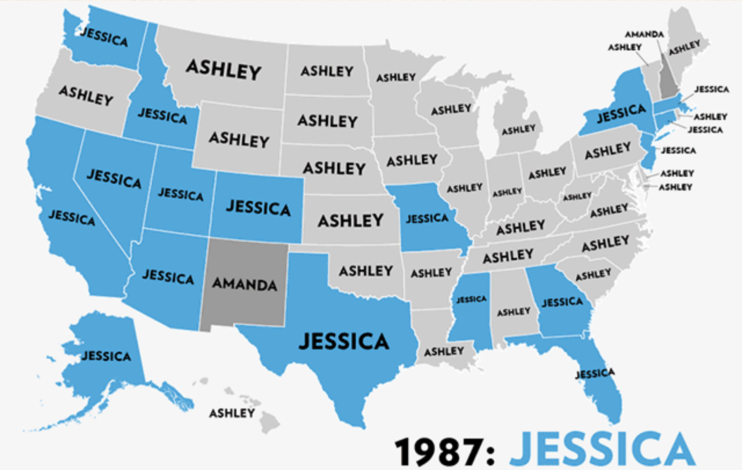

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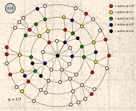

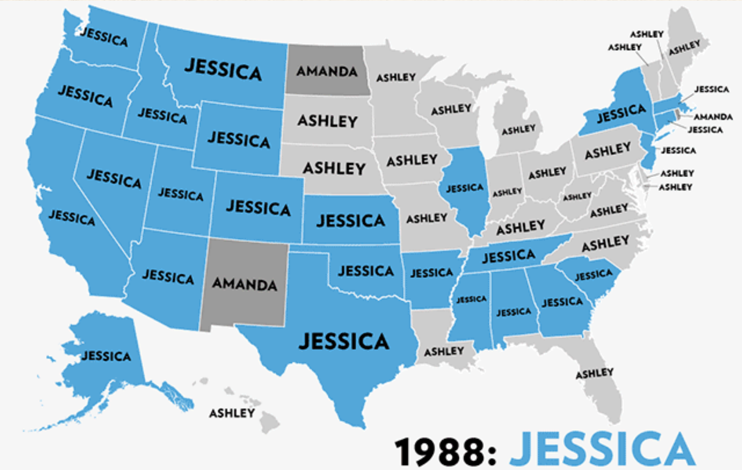

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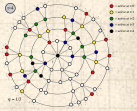

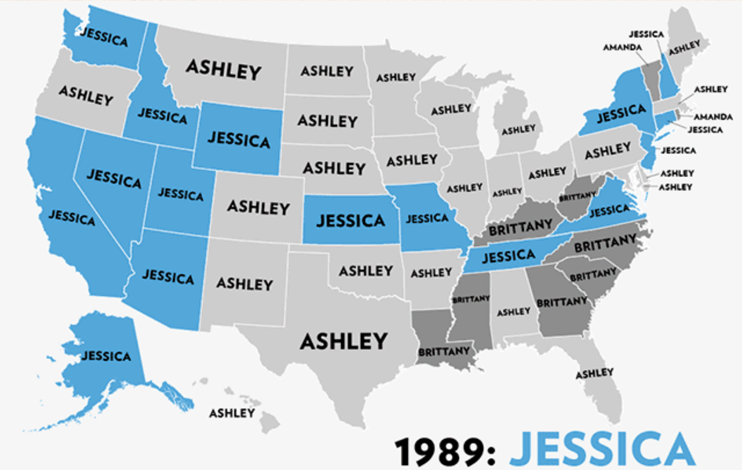

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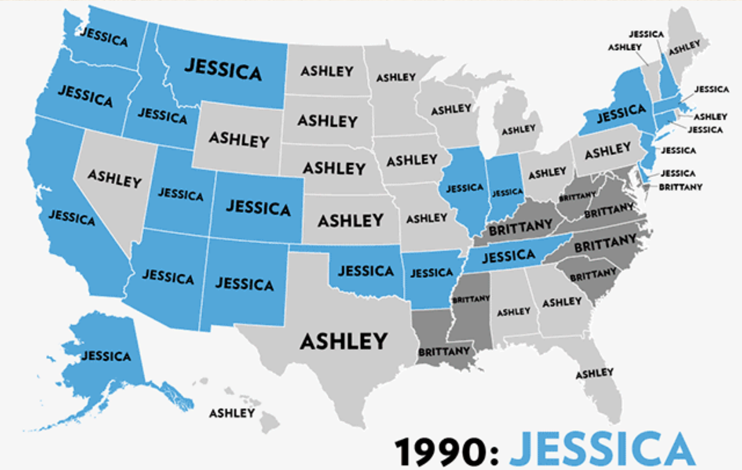

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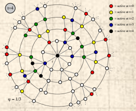

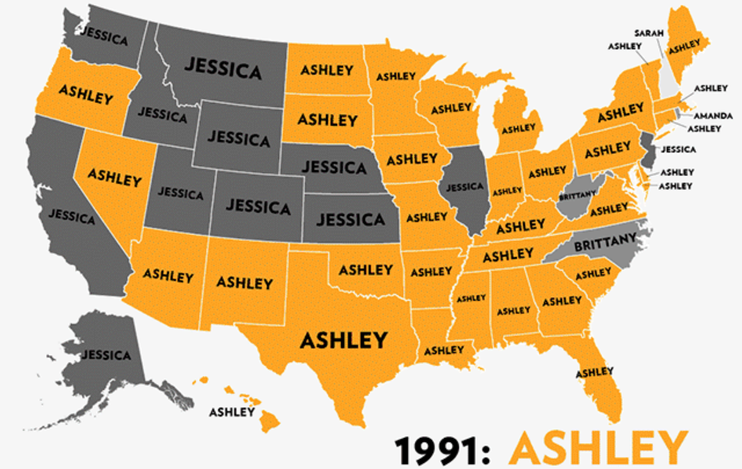

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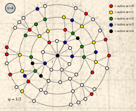

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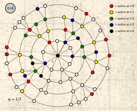

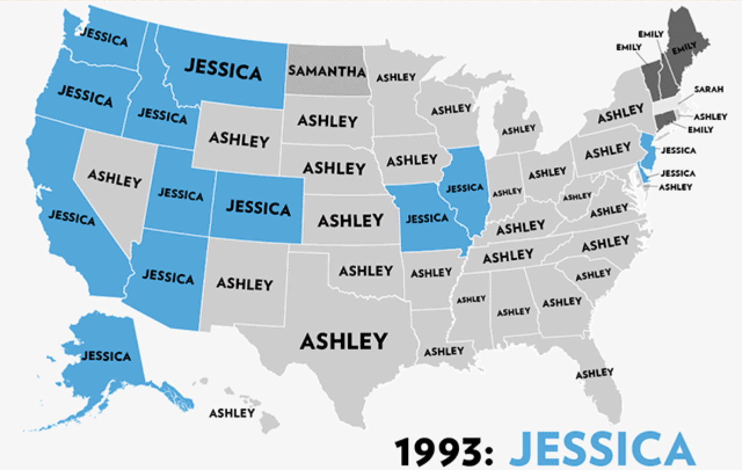

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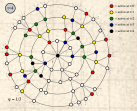

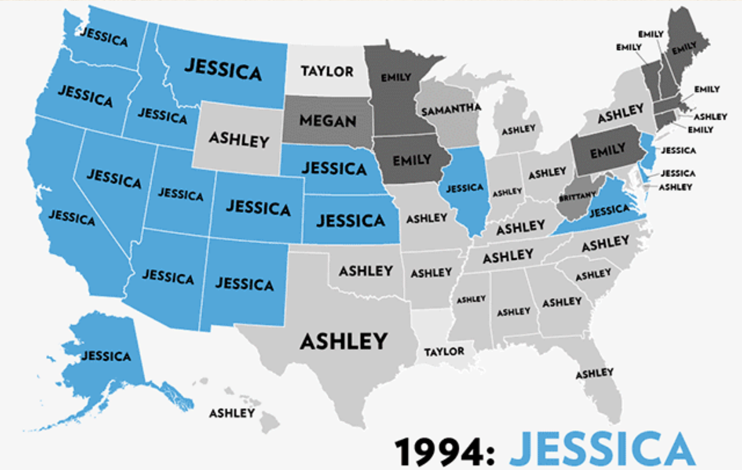

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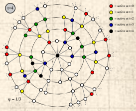

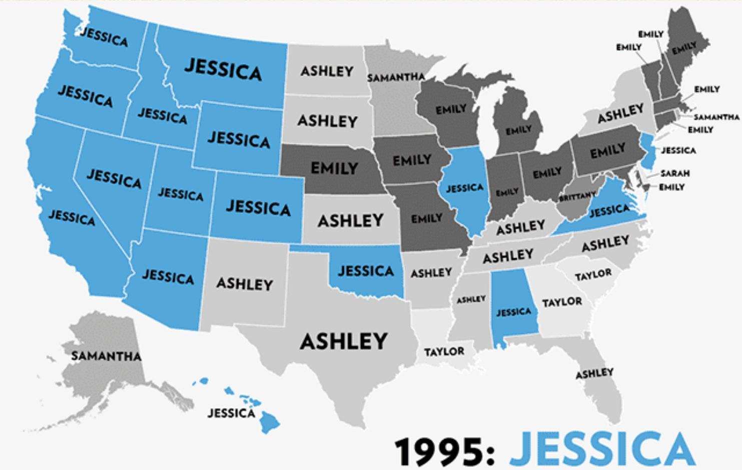

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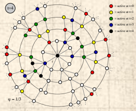

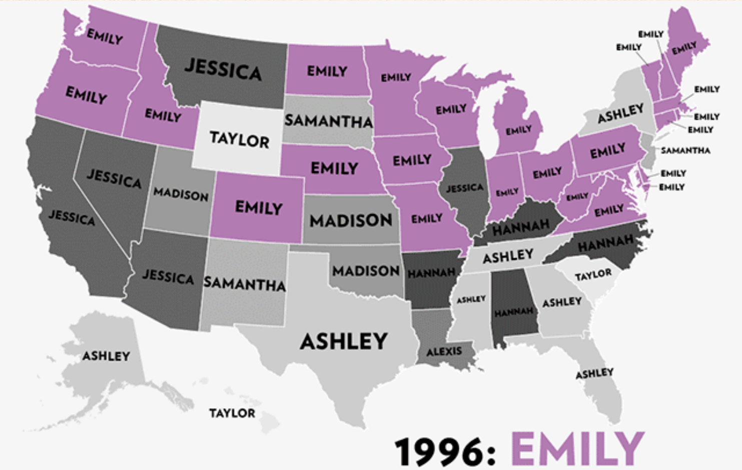

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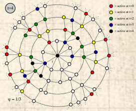

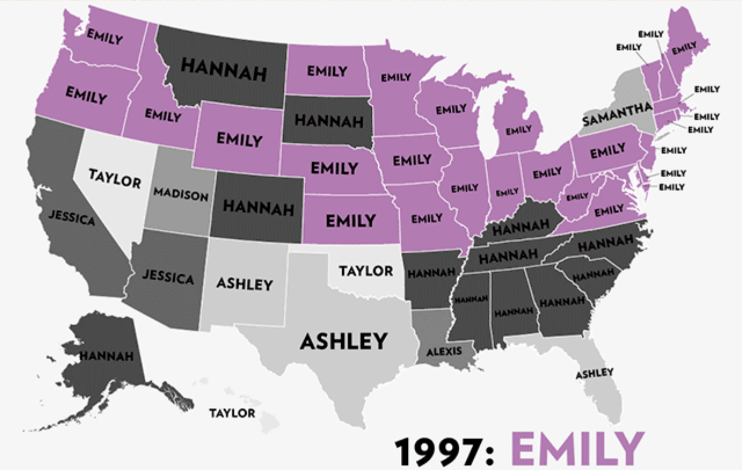

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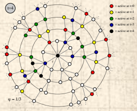

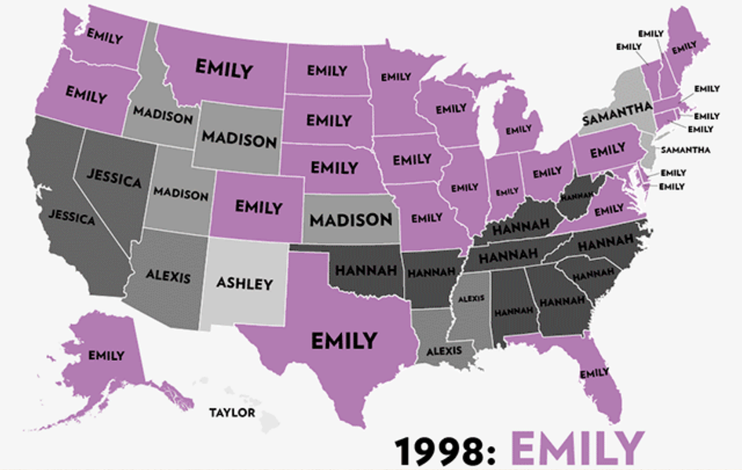

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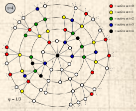

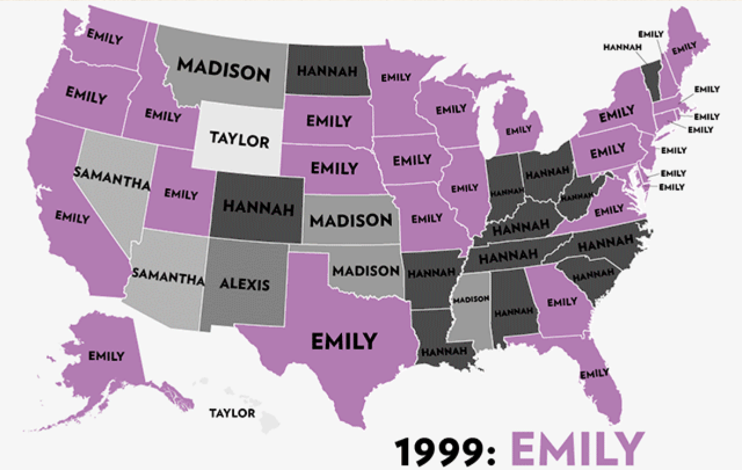

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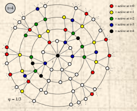

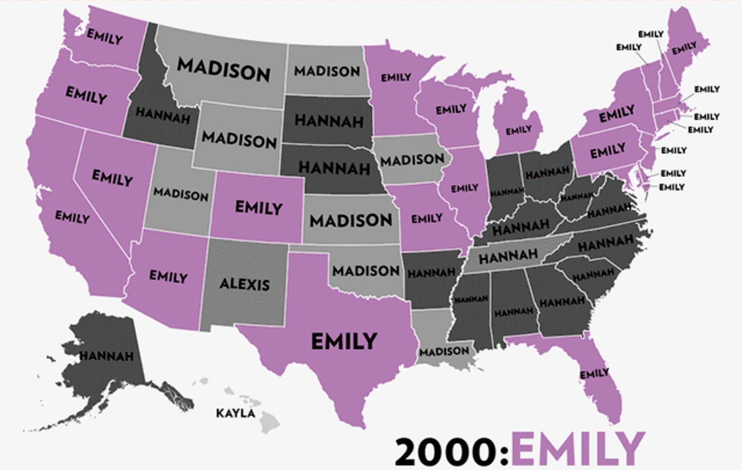

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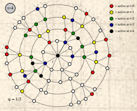

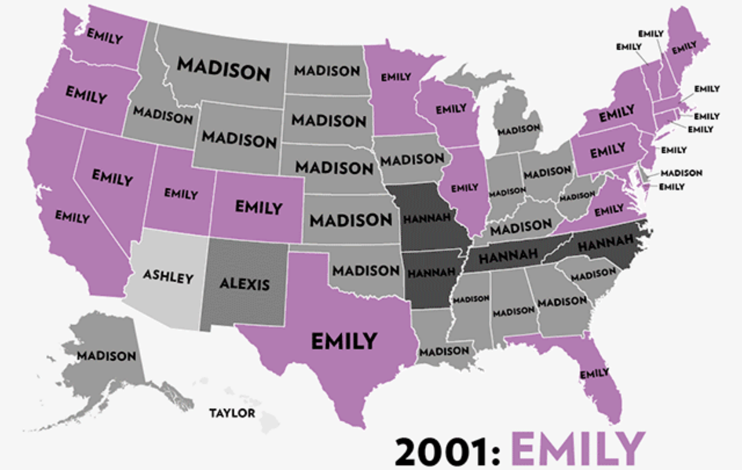

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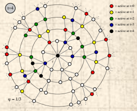

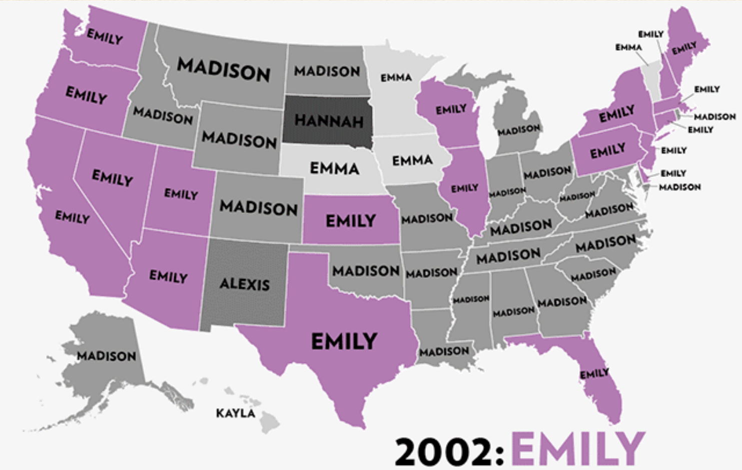

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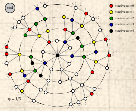

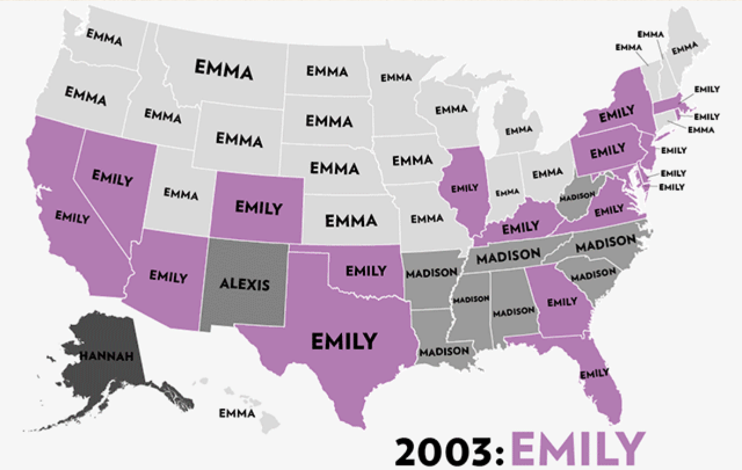

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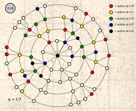

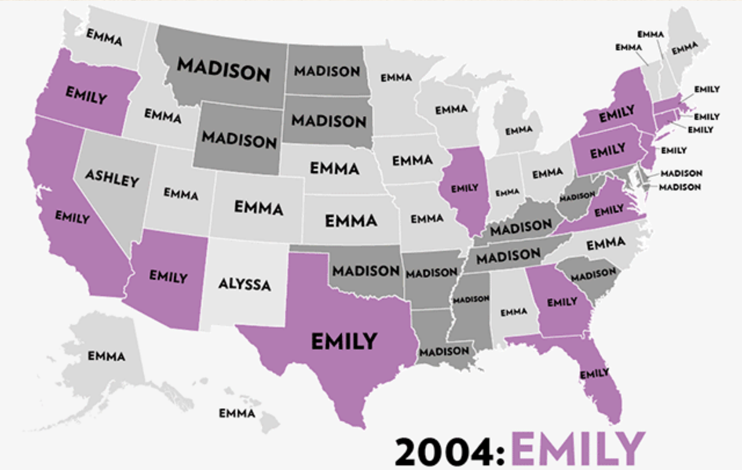

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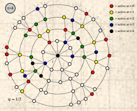

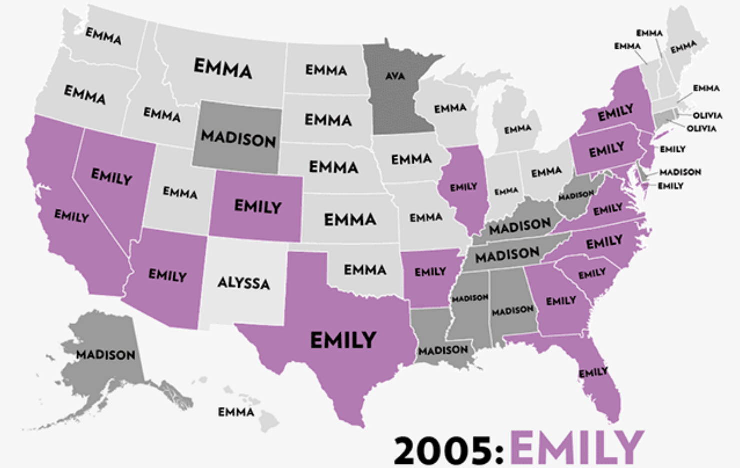

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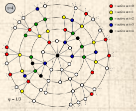

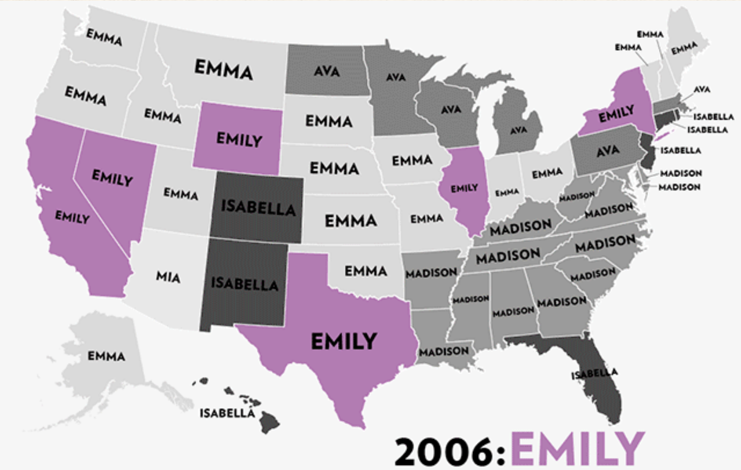

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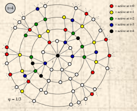

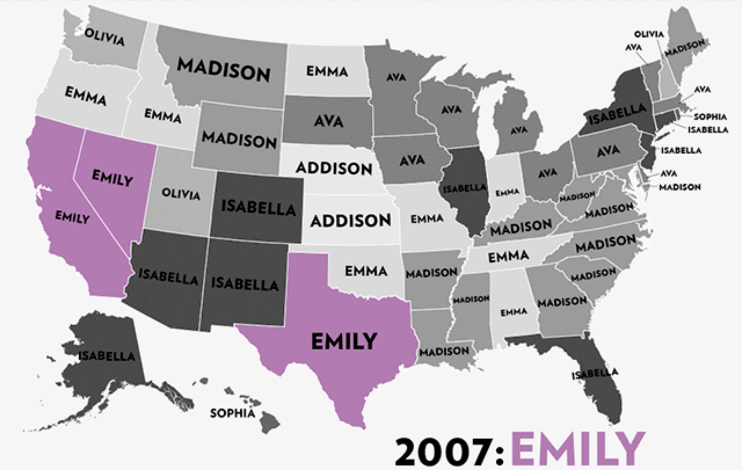

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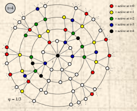

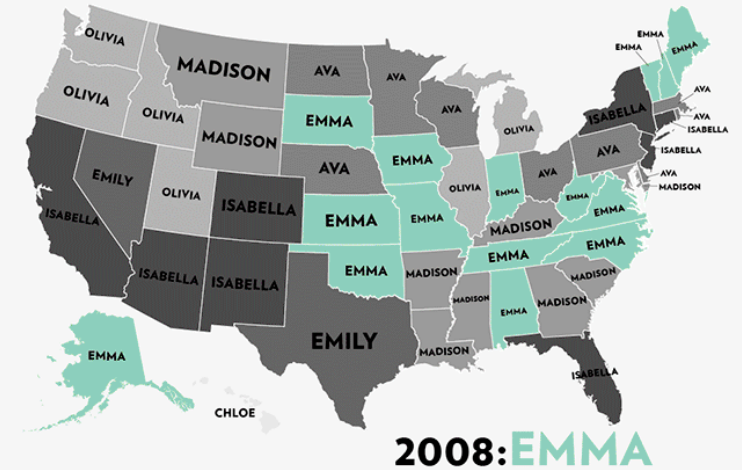

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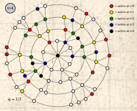

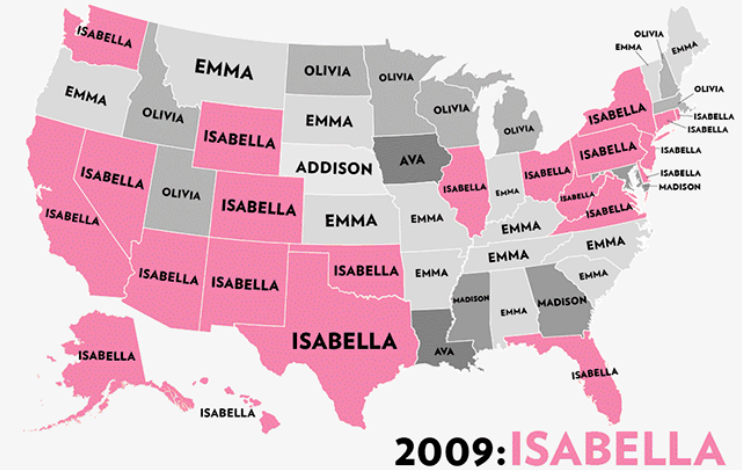

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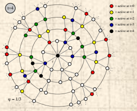

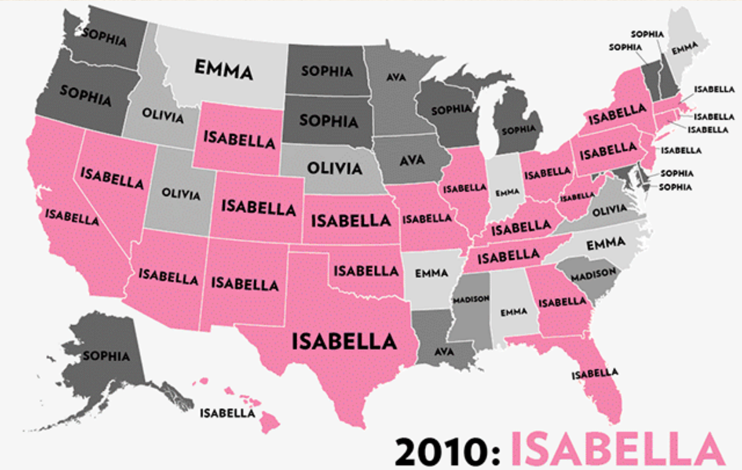

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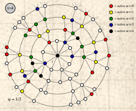

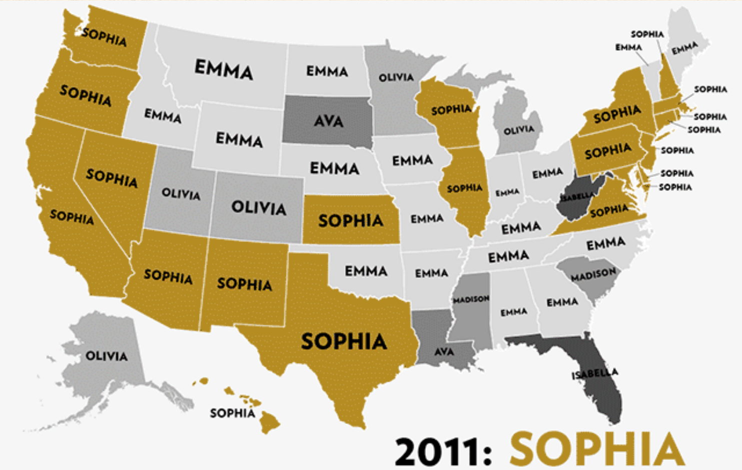

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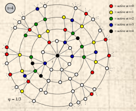

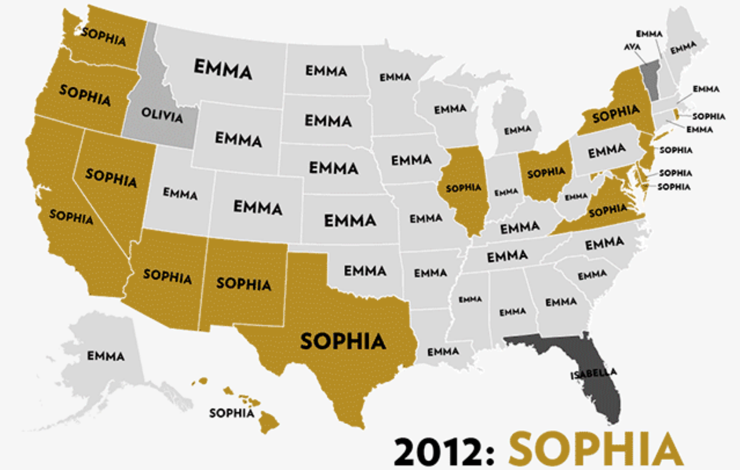

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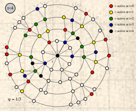
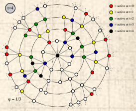
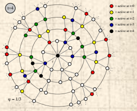


Richard Feynmann on the Social Sciences:



Sheldon Cooper on the Social Sciences:



Things that spread well:

buzzfeed.com:

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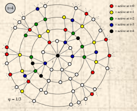

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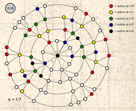
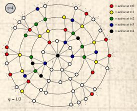
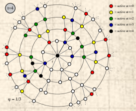


LOL + cute + fail + wtf:

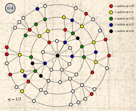
Please try reloading this page. If the problem persists let us know.



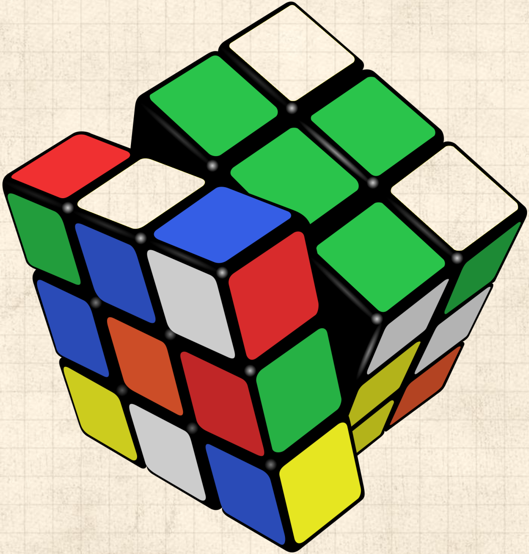
The whole lolcats thing:

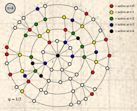


Some things really stick:

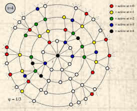


wtf + geeky + omg:

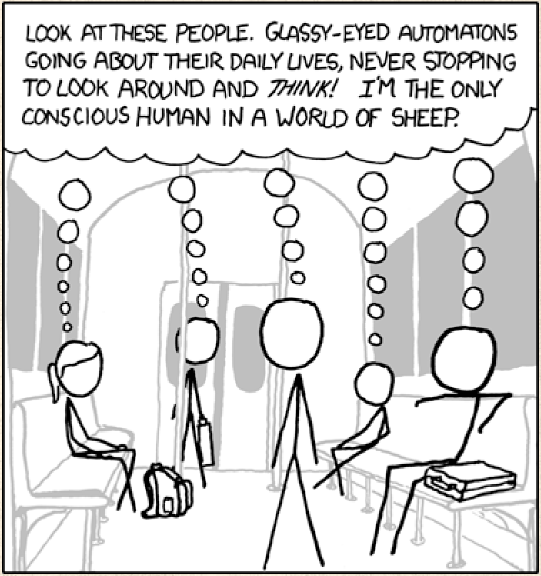




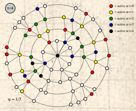
Outline



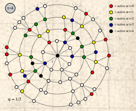
Why social contagion works so well:



http://xkcd.com/610/



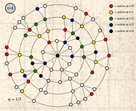
Social Contagion



Social Contagion

Examples abound

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



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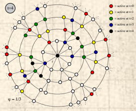

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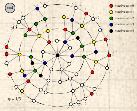
SIR and SIRS type contagion possible

- Classes of behavior versus specific behavior



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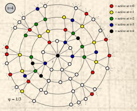
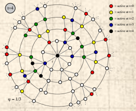


SIR and SIRS type contagion possible

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

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

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



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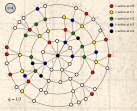

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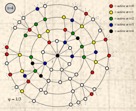
- Cindy Harrell appeared in the (terrifying) music video for Ray Parker Jr.'s Ghostbusters.
- In Stranger Things 2, Steve Harrington reveals his Fabergé secret.

Market much?

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

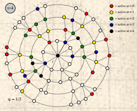
- Advertisement enjoyed during "Herstory of Dance", Community S4E08, April 2013.



Framingham heart study:

Evolving network stories (Christakis and Fowler):

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



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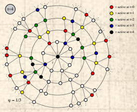

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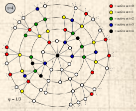

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Controversy:

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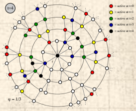

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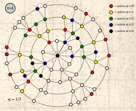
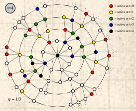
- Everything is contagious—Doubts about the social plague stir in the human superorganism (Dave Johns, Slate, April 8, 2010).



Social Contagion

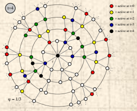
Two focuses for us



Social Contagion

Two focuses for us

- Widespread media influence



Social Contagion

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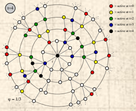

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Two focuses for us

- Widespread media influence
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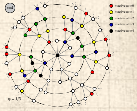
We need to understand influence



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Two focuses for us

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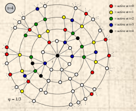
We need to understand influence

- Who influences whom?



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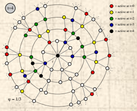
- Who influences whom? Very hard to measure...



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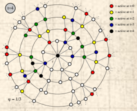

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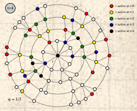

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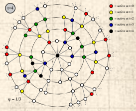

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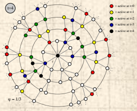
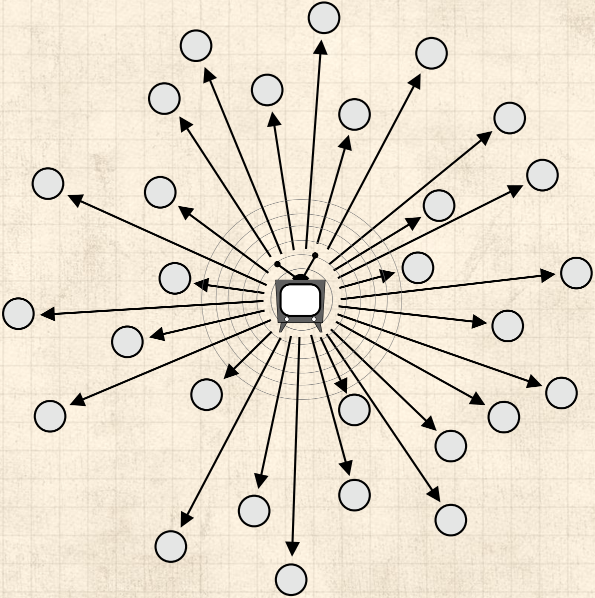
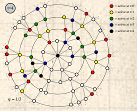
- The infectious idea of opinion leaders (Katz and Lazarsfeld) [19]

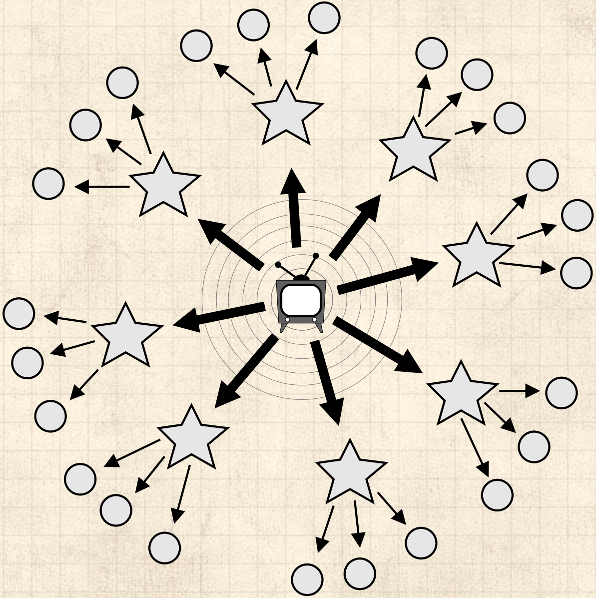


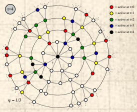
The hypodermic model of influence



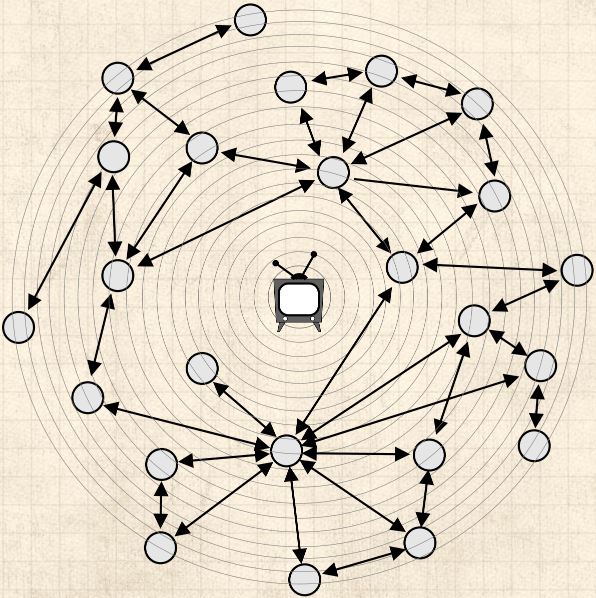


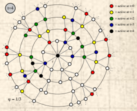
The two step model of influence [19]



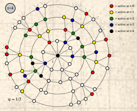


The general model of influence: the Social Wild

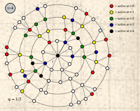




Talking about the social wild:



Why do things spread socially?



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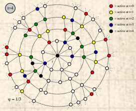

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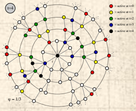

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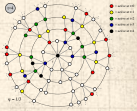

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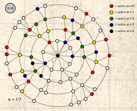

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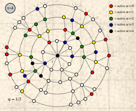

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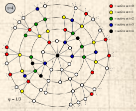

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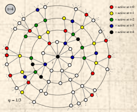

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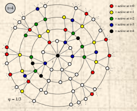

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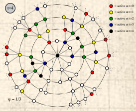
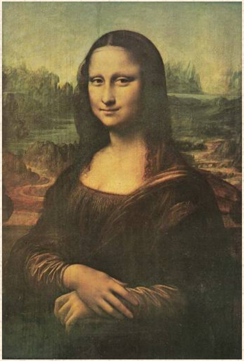
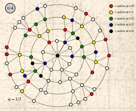
- Always good to examine what is said before and after the fact ...



The Mona Lisa



- "Becoming Mona Lisa: The Making of a Global Icon"—David Sassoon



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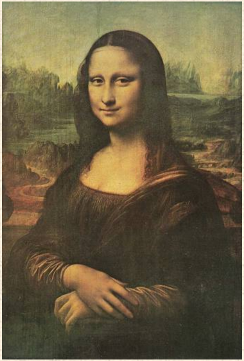

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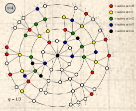

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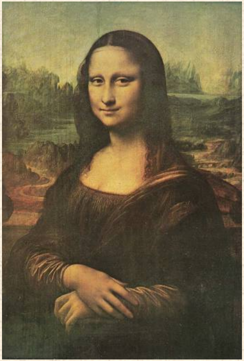

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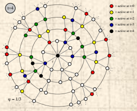

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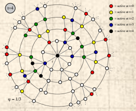
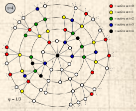


The Mona Lisa



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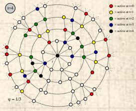
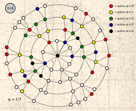


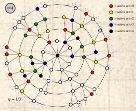
'Tattooed Guy' Was Pivotal in Armstrong Case [nytimes]

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

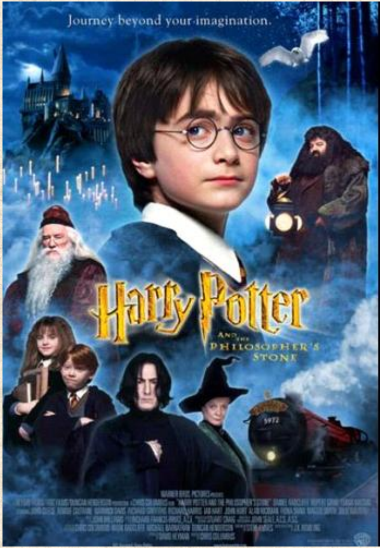


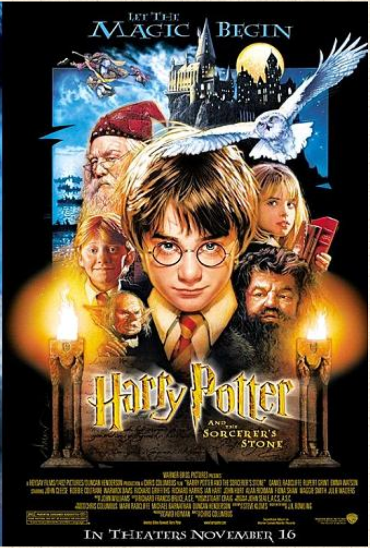
The completely unpredicted fall of Eastern Europe:

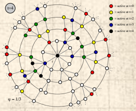
Timunr Kuran: [20, 21] "Now Out of Never: The Element of Surprise in the East European Revolution of 1989"



The dismal predictive powers of editors...







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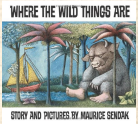

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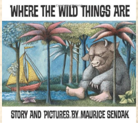

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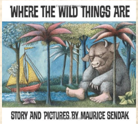

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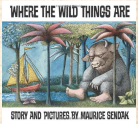

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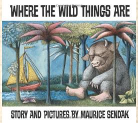

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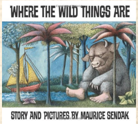

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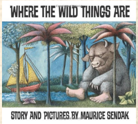

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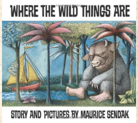

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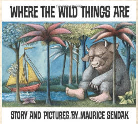

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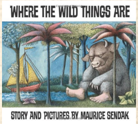

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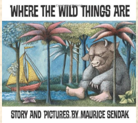

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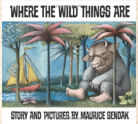

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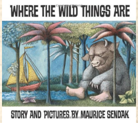

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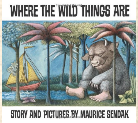

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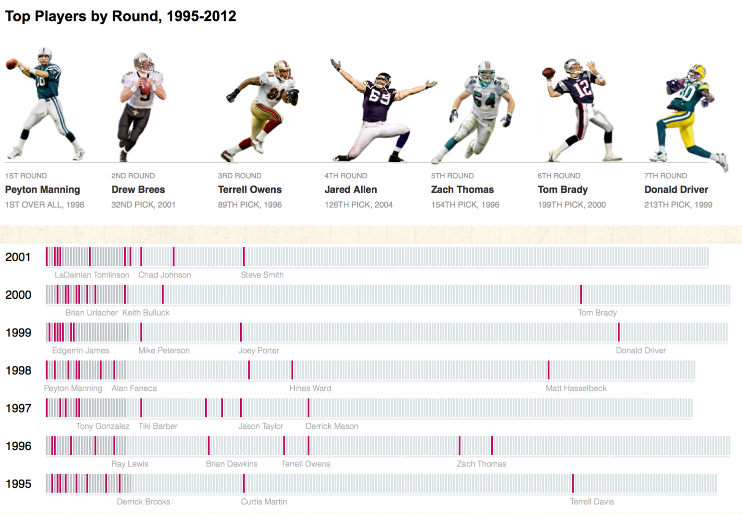
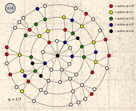
Drafting success in the NFL:



Social Contagion

Messing with social connections



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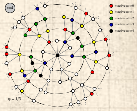

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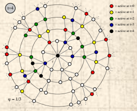

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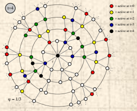

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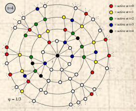

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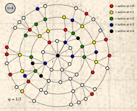

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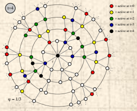

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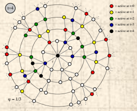

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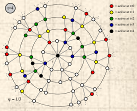

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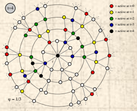

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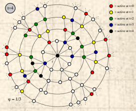

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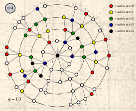

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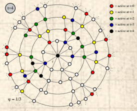

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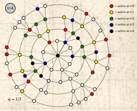

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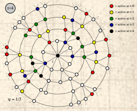

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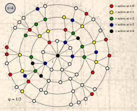

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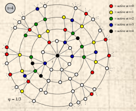

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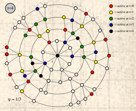

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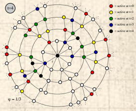

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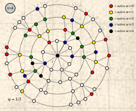

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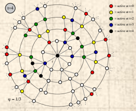

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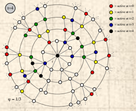

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- Conspicuous Destruction (Potlatch)


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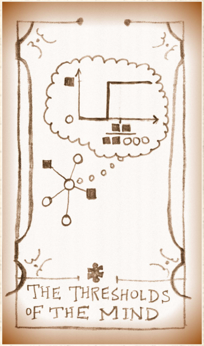
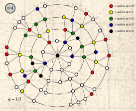
THE STORIES AND THE TROPES
THE TRUTH OF DIFFUSION
THE UNVEILING OF HIDDEN POWERS
THE SCRYING FOR THE SHAPES OF THINGS
THE LIMITS OF ORGANIZATIONS
THE OVERCOMING OF CATASTROPHE
THE TROUBLES ILL-FORMED
THE NETWORKS OF MANY ILKS
THE CHAOS OF FETTERED CONTAGION
THE END


THE THRESHOLDS OF THE MIND

Social Contagion



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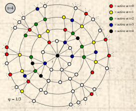

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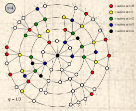

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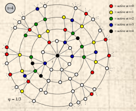

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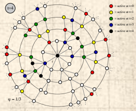

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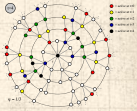

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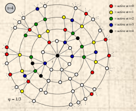

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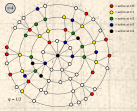
  - Social learning theory, Informational cascades,...



Social contagion models

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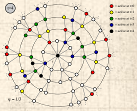

Social contagion models

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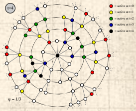
- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted



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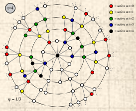

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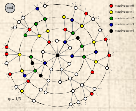

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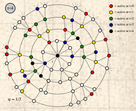

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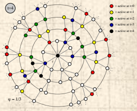

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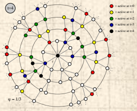

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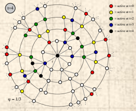

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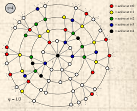

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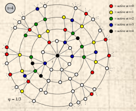

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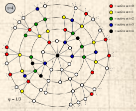

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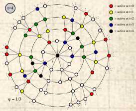

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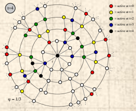

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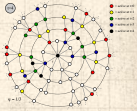

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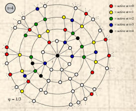

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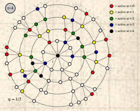
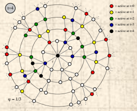
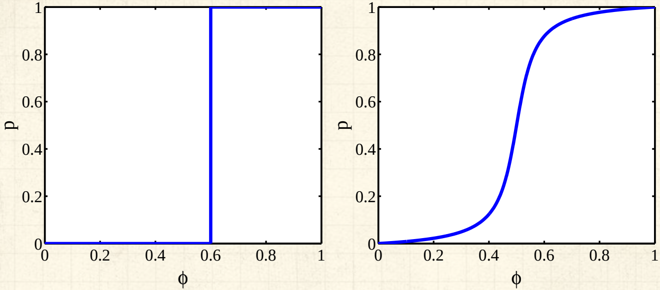
  - An individual's utility increases with the adoption level among peers and the population in general



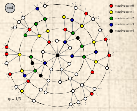


Outline

Threshold models—response functions



- Example threshold influence response functions: deterministic and stochastic



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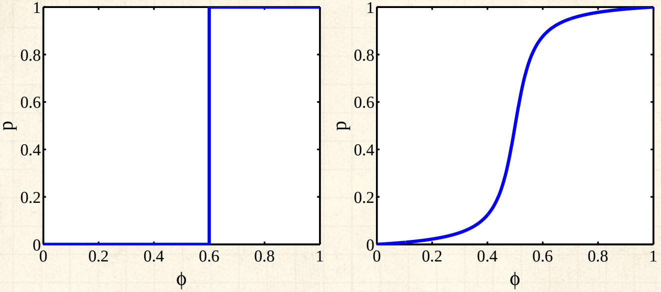

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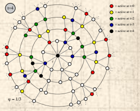
- ϕ = fraction of contacts 'on' (e.g., rioting)



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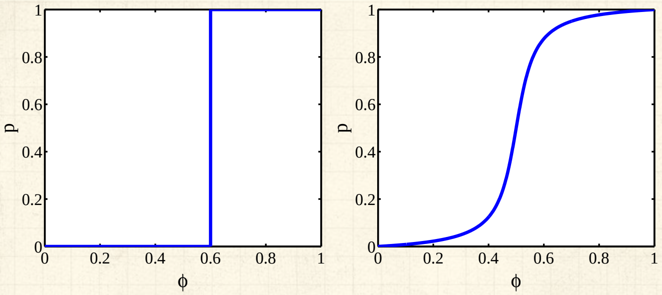

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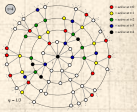
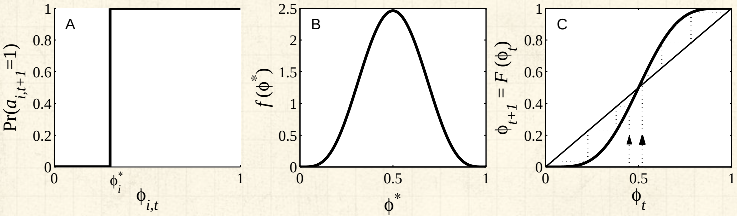


Threshold models

Action based on perceived behavior of others:



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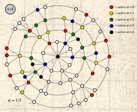

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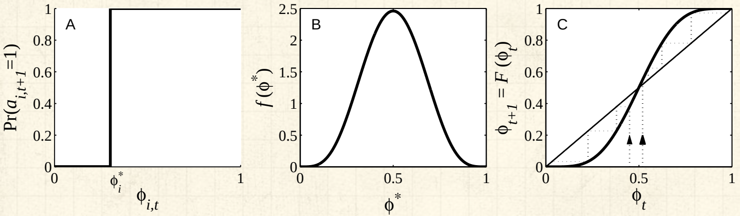

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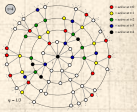

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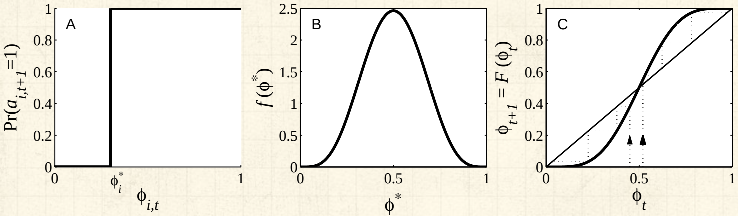

- Two states: S and I.
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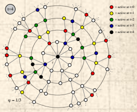
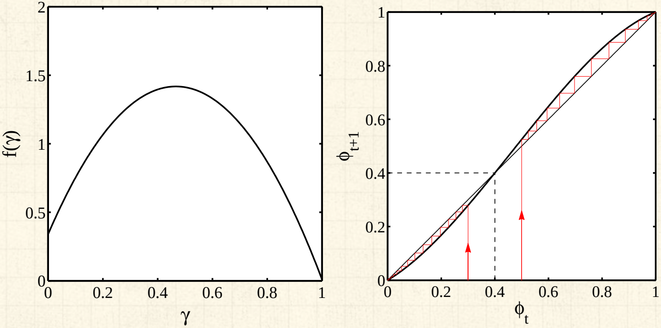
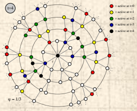
- This is a Critical mass model



Threshold models

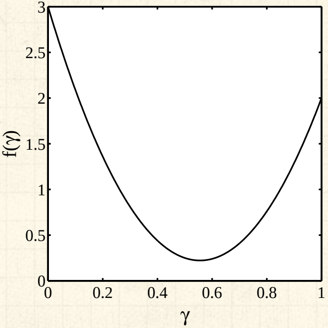
Another example of critical mass model:

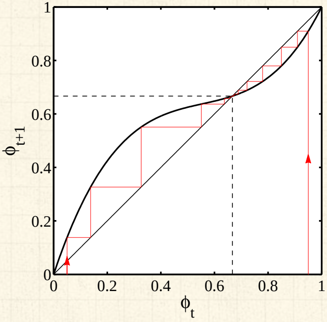


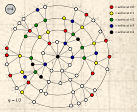


Threshold models

Example of single stable state model:







Threshold models

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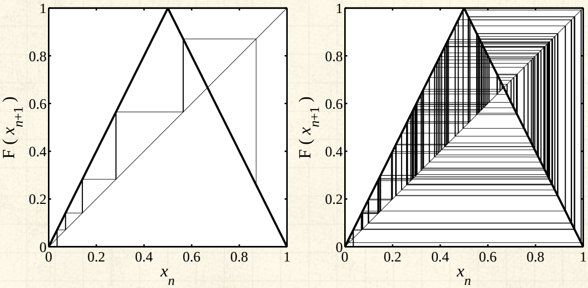

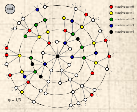

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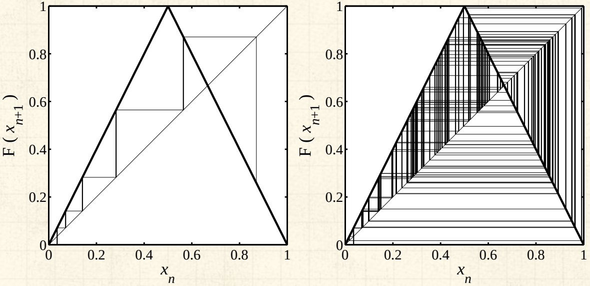

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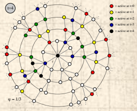

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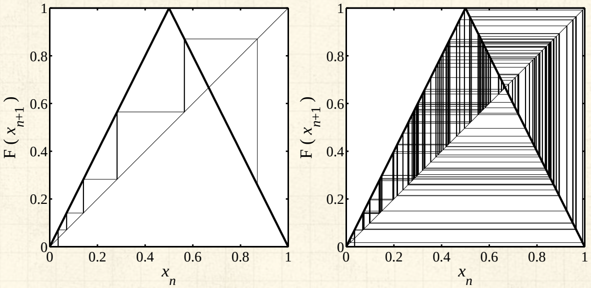

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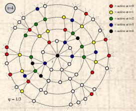
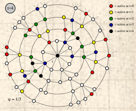
- Synchronous update assumption is crucial



Threshold models—Nutshell

Implications for collective action theory:



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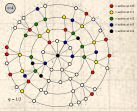
Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity



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Implications for collective action theory:

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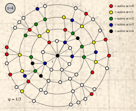
2. Small individual changes $\Rightarrow$ large global changes



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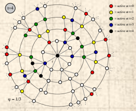

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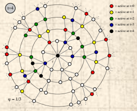

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2. Small individual changes $\Rightarrow$ large global changes
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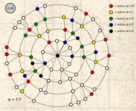
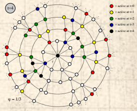
4. System stories live in left null space of our stories—we can't even see them.
5. But we happily impose simplistic, individual-centric stories—we can't help ourselves.



Outline



Many years after Granovetter and Soong's work:

- "A simple model of global cascades on random networks"
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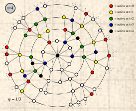

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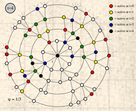

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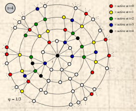

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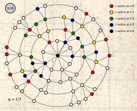
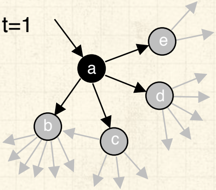
We'll also explore:

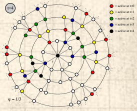
- "Seed size strongly affects cascades on random networks" [14]
  Gleeson and Cahalane, Phys. Rev. E, 2007.
- "Direct, phyiscally motivated derivation of the contagion condition for spreading processes on generalized random networks" [10] Dodds, Harris, and Payne, Phys. Rev. E, 2011
- "Influentials, Networks, and Public Opinion Formation" [27]
  Watts and Dodds, J. Cons. Res., 2007.



Threshold model on a network



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



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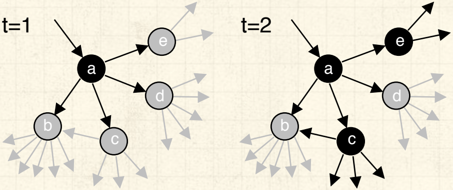

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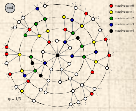

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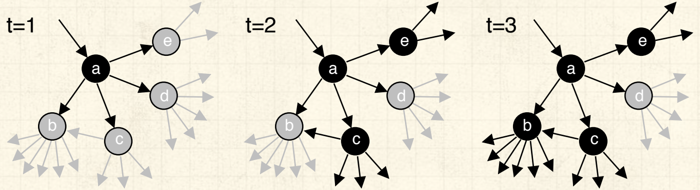

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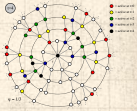
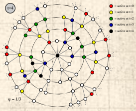


Threshold model on a network

- Interactions between individuals now represented by a network.



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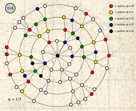

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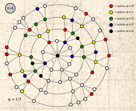

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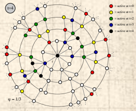

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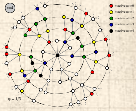

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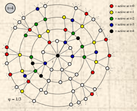

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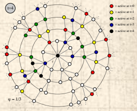

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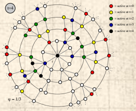

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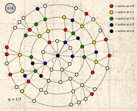
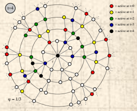
- Individuals remain active when switched (no recovery = SI model).



Snowballing

First study random networks:



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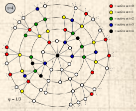
- Start with N nodes with a degree distribution P_k



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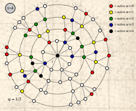
- Nodes are randomly connected (carefully so)



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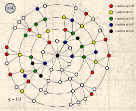

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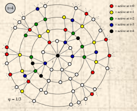
- Determine a cascade condition



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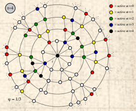
The Cascade Condition:

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



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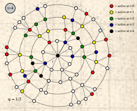
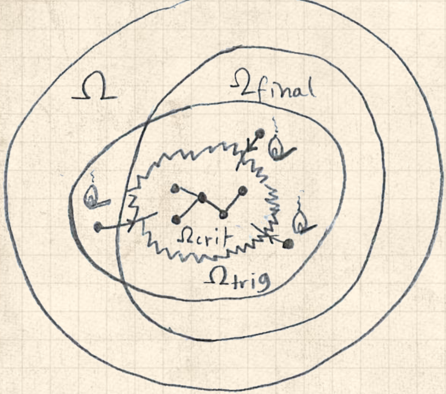
The Cascade Condition:

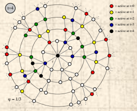
1. If one individual is initially activated, what is the probability that an activation will spread over a network?
2. What features of a network determine whether a cascade will occur or not?



Example random network structure:



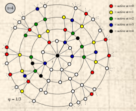
- $\Omega_{crit} = \Omega_{vuln}$ = critical mass = global vulnerable component
- Ω_{trig} = triggering component
- Ω_{final} = potential extent of spread
- Ω = entire network



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

Snowballing

Follow active links



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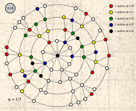
- An active link is a link connected to an activated node.



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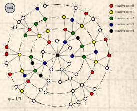
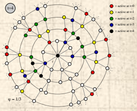


Snowballing

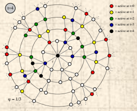
Follow active links

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



The most gullible

Vulnerables:



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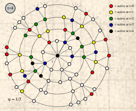

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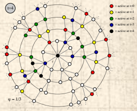

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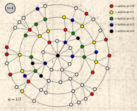

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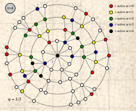

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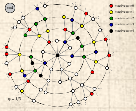

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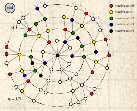
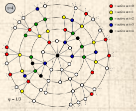
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.



Cascade condition

Back to following a link:



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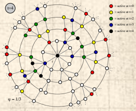

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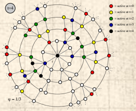

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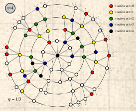
$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle$$



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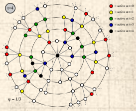
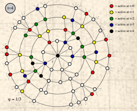
- So

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



Cascade condition

Next: Vulnerability of linked node



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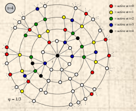
$$\beta_k = \int_{\phi_*'=0}^{1/k} f(\phi_*')\mathrm{d}\phi_*'$$



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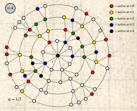

Cascade condition

Next: Vulnerability of linked node

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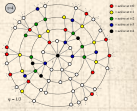
$$\beta_k = \int_{\phi_*'=0}^{1/k} f(\phi_*')\mathrm{d}\phi_*'$$

- 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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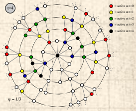

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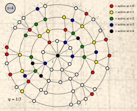

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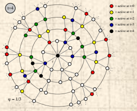
$$R = \left[\underbrace{\sum_{k=1}^{\infty} (k-1) \cdot \beta_k \cdot \frac{kP_k}{\langle k \rangle}}_{\text{success}} + \underbrace{0 \cdot (1-\beta_k) \cdot \frac{kP_k}{\langle k \rangle}}_{\text{failure}} \right]$$



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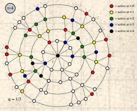
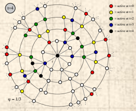


Cascade condition

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

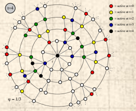
$$\sum_{k=1}^{\infty}(k-1)\cdot\beta_k\cdot\frac{kP_k}{\langle k\rangle} > 1.$$

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



Cascade condition

Two special cases:



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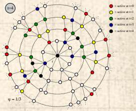
Two special cases:

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



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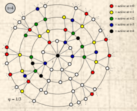
$$\beta \cdot \sum_{k=1}^{\infty} (k-1) \cdot \frac{k P_k}{\langle k \rangle} > 1.$$



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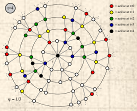

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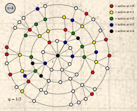
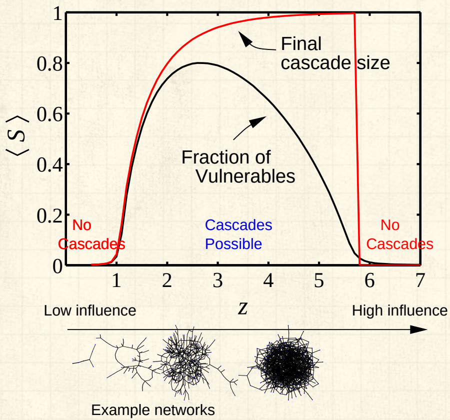
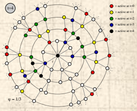


Cascades on random networks



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



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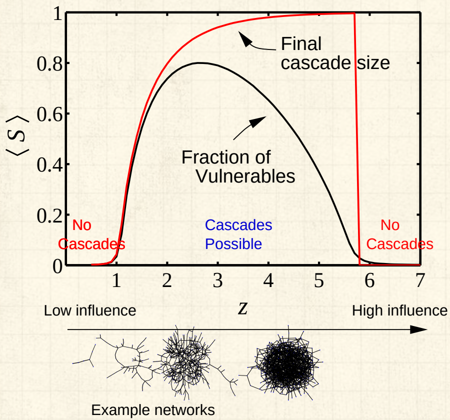

- Cascades occur only if size of max vulnerable cluster > 0.
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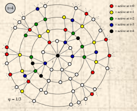

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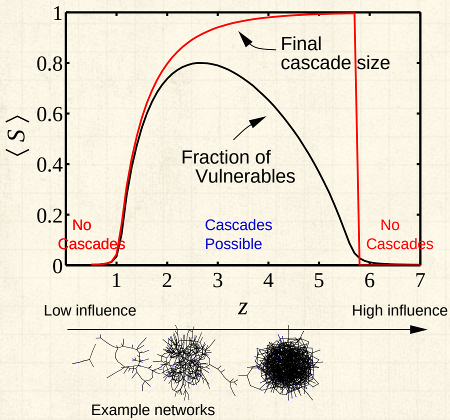

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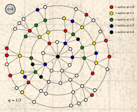
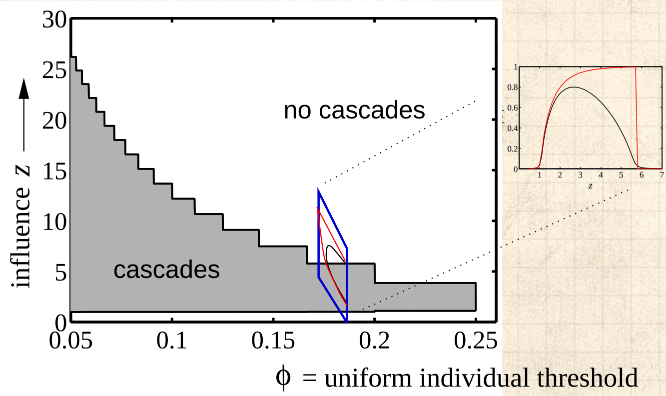
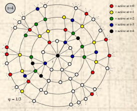
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.



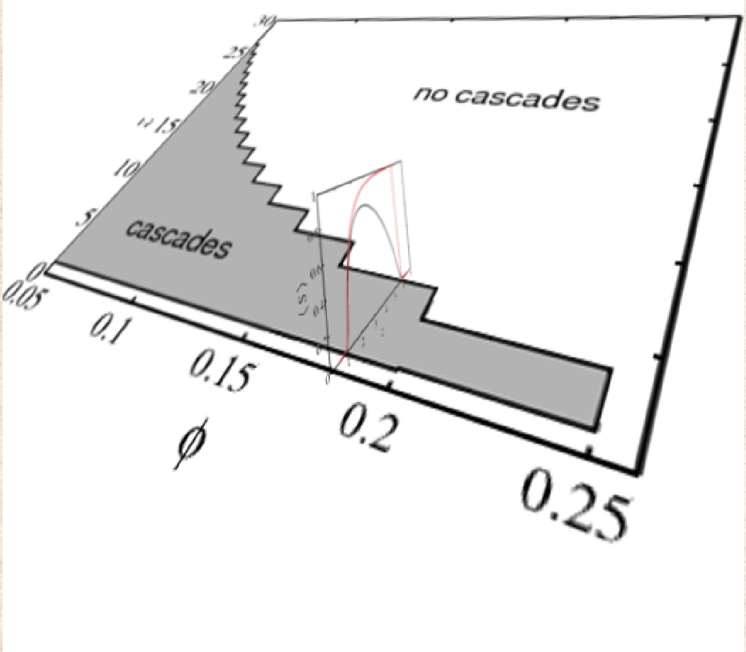
Cascade window for random networks

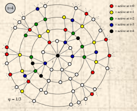




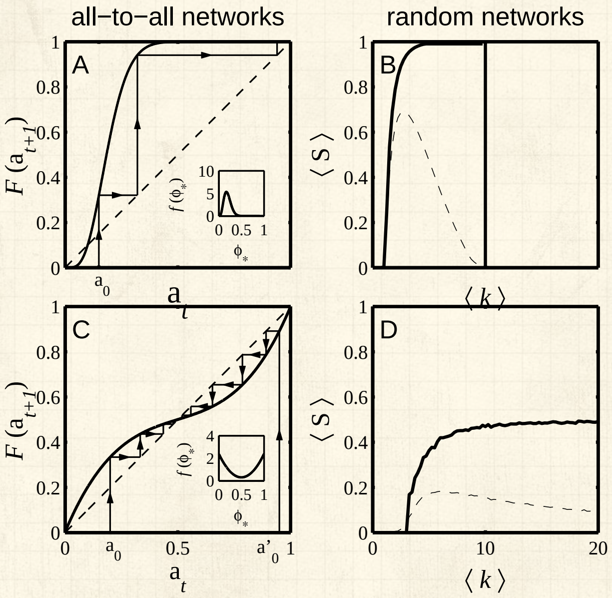
- 'Cascade window' widens as threshold ϕ decreases.
- Lower thresholds enable spreading.

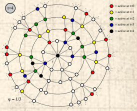
Cascade window for random networks





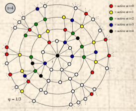
All-to-all versus random networks





Cascade window—summary

For our simple model of a uniform threshold:



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For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks.
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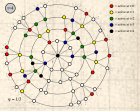

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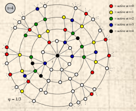

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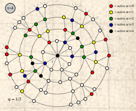
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists.
   Cascades are possible in "Cascade window."



Outline

Social Contagion Models

Background

Granovetter's model

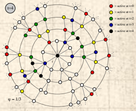
Network version

Final size

Spreading success

Groups

References



Threshold contagion on random networks

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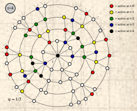

Threshold contagion on random networks

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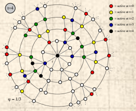

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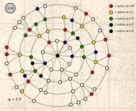

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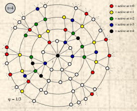

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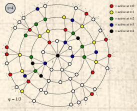
- Developed further by Gleeson in "Cascades on correlated and modular random networks," Phys. Rev. E, 2008. [13]



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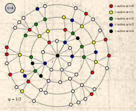

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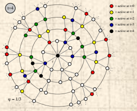
- Capitalize on local branching network structure of random networks (again)



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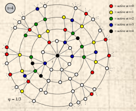

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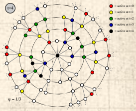

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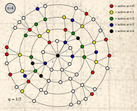

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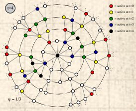

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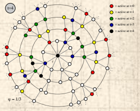
  - $t = n$: enough nodes within n hops of i switched on at $t = 0$ and their effects have propagated to reach i.



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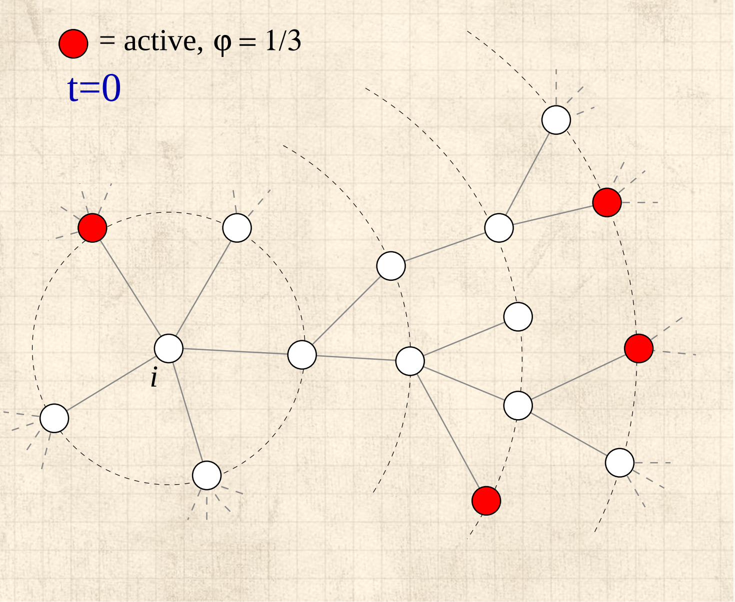

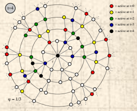

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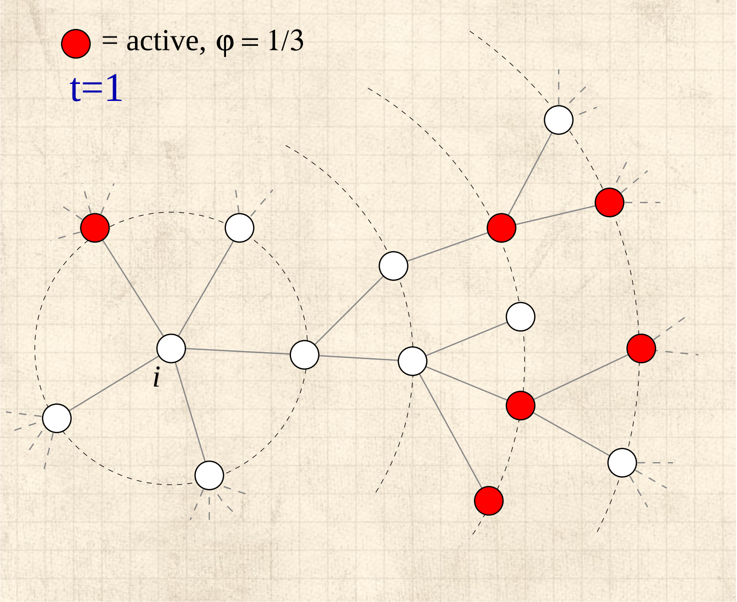

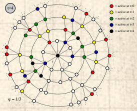

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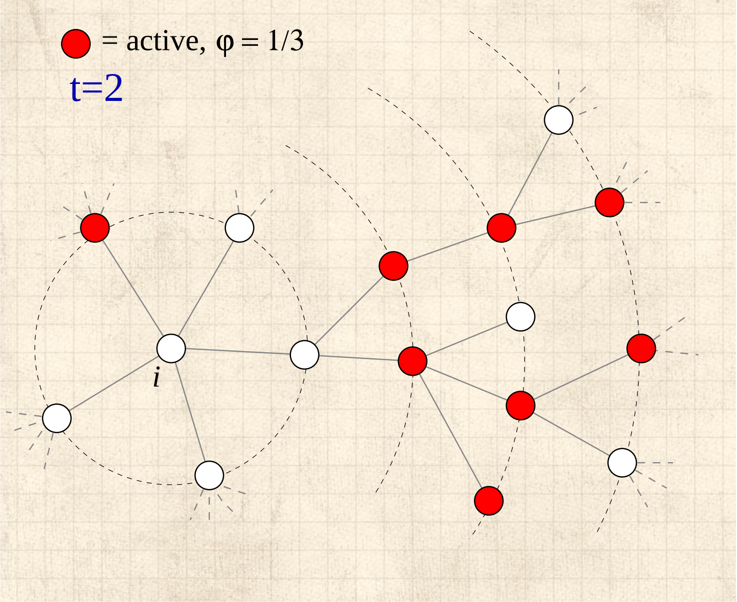

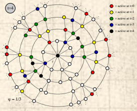

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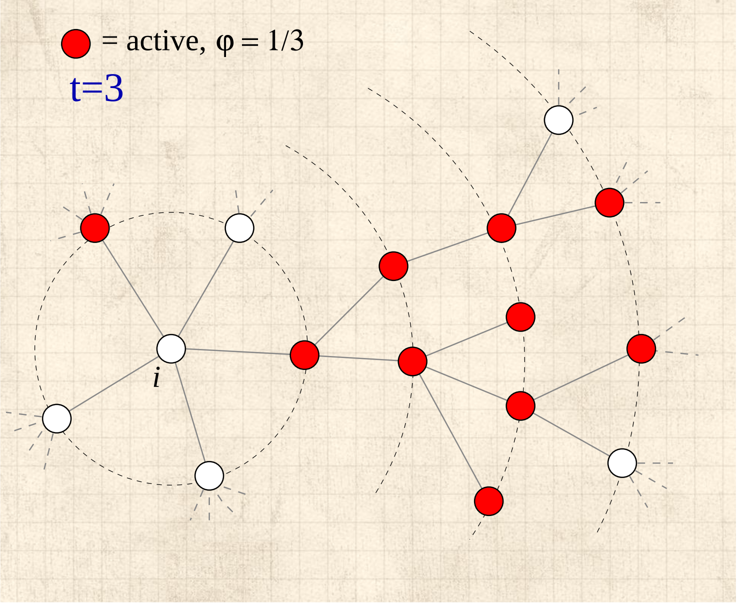

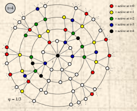

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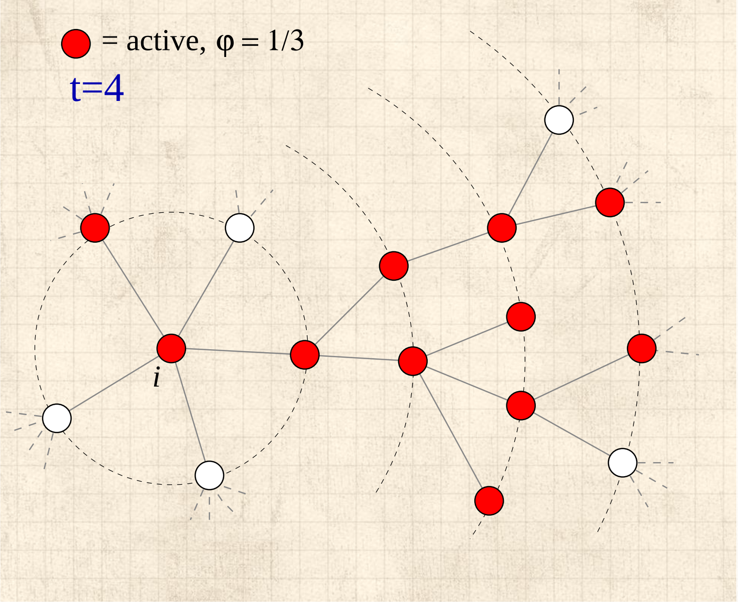

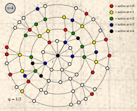

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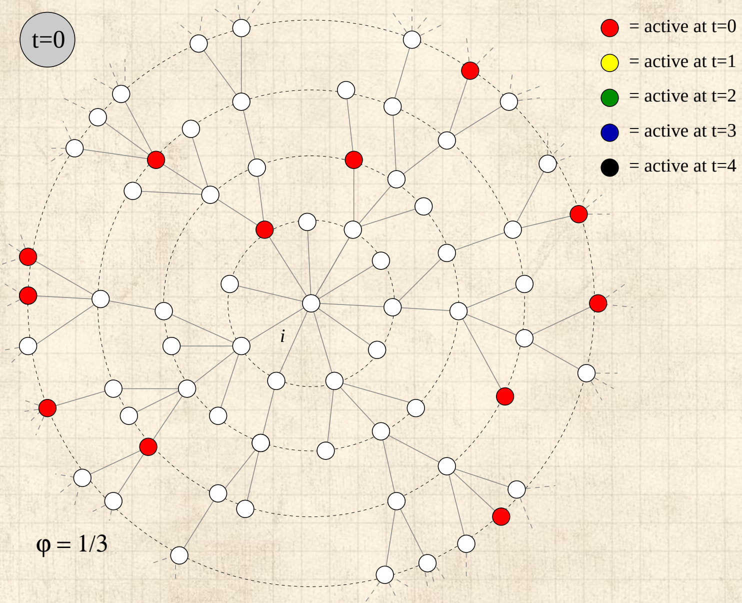

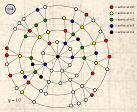

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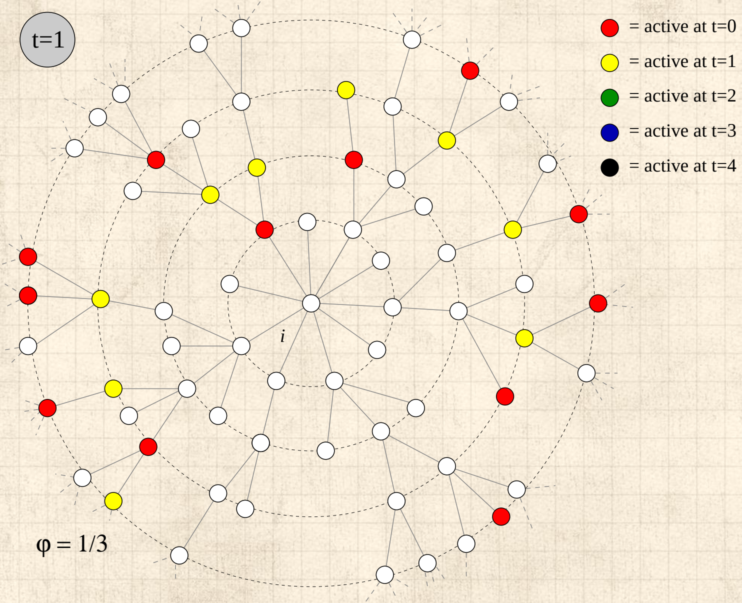

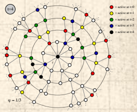

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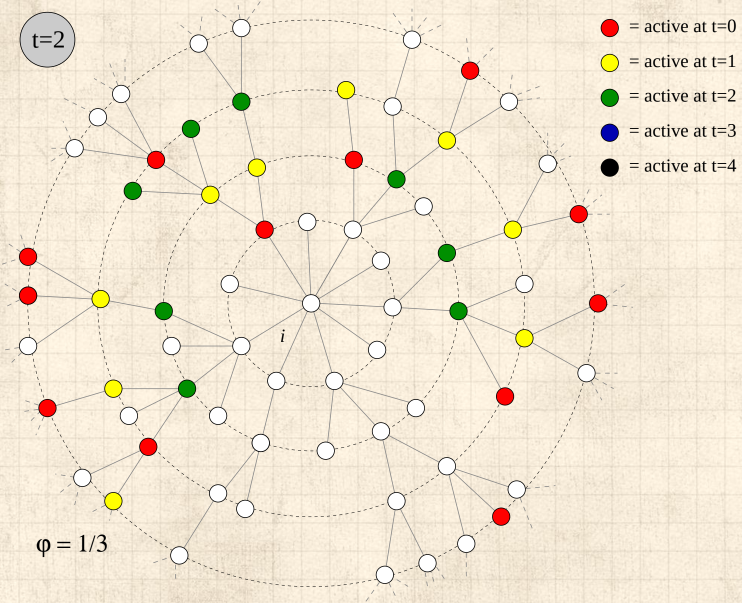

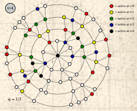

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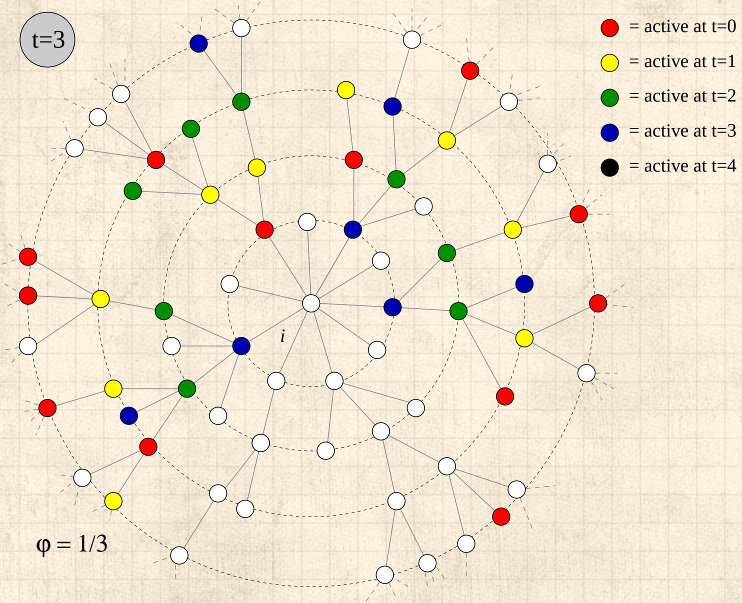

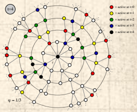

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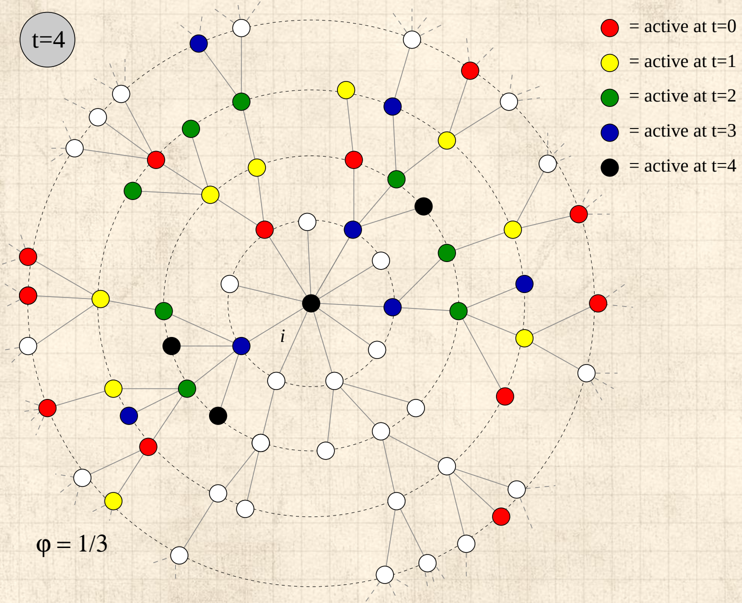

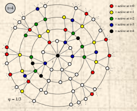

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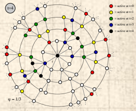

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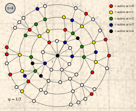

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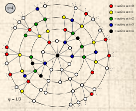

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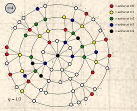

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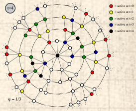
- Asynchronous updating can be handled too.



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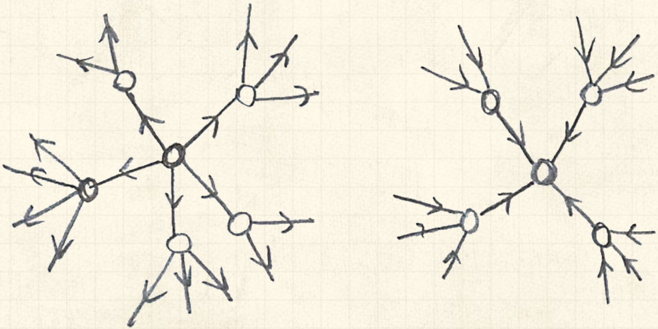
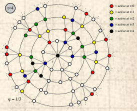
Pleasantness:

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





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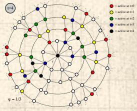
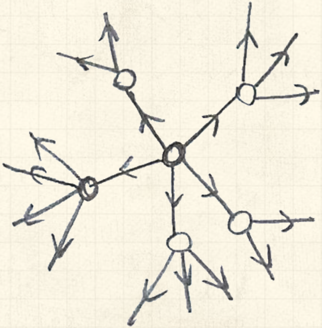
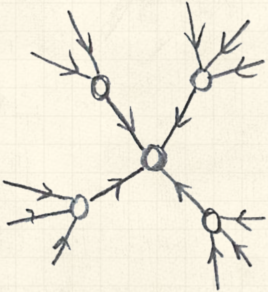


Pleasantness:

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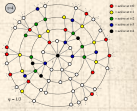
- **Notation:**
  $\phi_{k,t} = \mathbf{Pr}$(a degree k node is active at time t).



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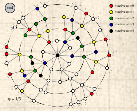

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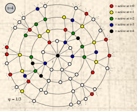

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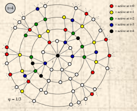

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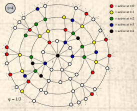

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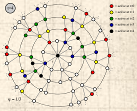

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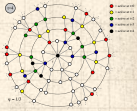
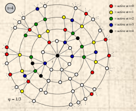
- Combining everything, we have:

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



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



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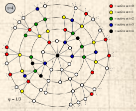

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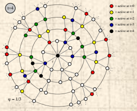

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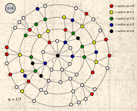
$$\phi_{i,t+1} = \phi_0 + (1 - \phi_0) \sum_{j=0}^{k_i} \binom{k_i}{j} \theta_t^{\,j} (1 - \theta_t)^{k_i - j} B_{k_i j}.$$



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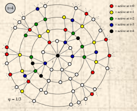

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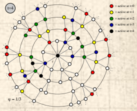

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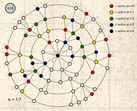

- So we need to compute θ_t... massive excitement...

Expected size of spread

First connect θ_0 to θ_1:

- $\theta_1 = \phi_0 +$

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

- $\frac{k P_k}{\langle k \rangle} = R_k$ = **Pr** (edge connects to a degree k node).
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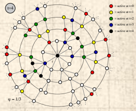
- ϕ_0 and $(1-\phi_0)$ terms account for state of node at time $t = 0$.



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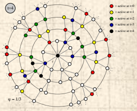
- See this all generalizes to give θ_{t+1} in terms of θ_t...



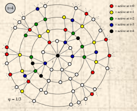
Expected size of spread

Two pieces: edges first, and then nodes

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

   with $\theta_0 = \phi_0$.

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



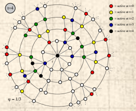
Expected size of spread

Iterative map for θ_t is key:

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

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

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



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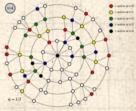
- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \to 0$.



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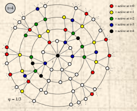
- Depends on map $\theta_{t+1} = G(\theta_t; \phi_0)$.



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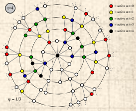
$$G(0;\phi_0) = \sum_{k=1}^{\infty} \frac{k P_k}{\langle k \rangle} \bullet B_{k0} > 0.$$

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



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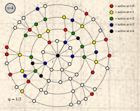
- If $\theta = 0$ is a fixed point of G (i.e., $G(0;\phi_0) = 0$) then spreading occurs if

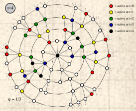
$$G'(0;\phi_0) = \sum_{k=0}^{\infty} \frac{kP_k}{\langle k \rangle} \bullet (k-1) \bullet B_{k1} > 1.$$



Expected size of spread:

In words:

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



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In words:

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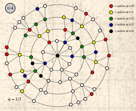
- If G has an unstable fixed point at $\theta = 0$, then cascades are also always possible.



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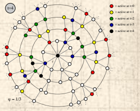

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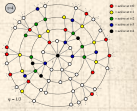

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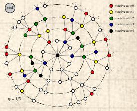

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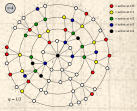
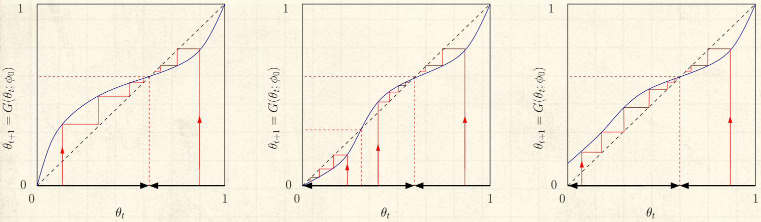
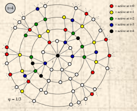
- A version of a critical mass model again.



General fixed point story:



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



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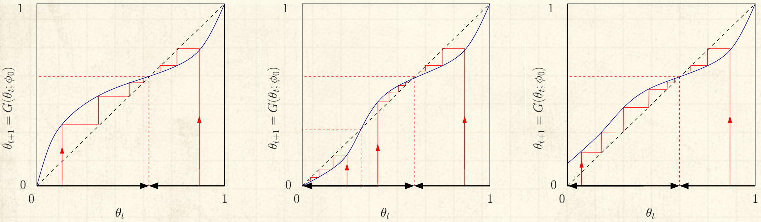
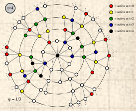


- Given $\theta_0 (= \phi_0)$, θ_∞ will be the nearest stable fixed point, either above or below.
- n.b., adjacent fixed points must have opposite stability types.



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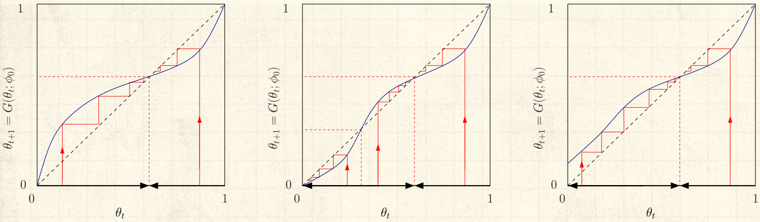

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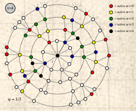

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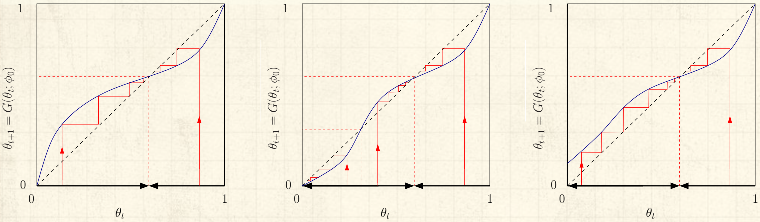

- Given $\theta_0 (= \phi_0)$, θ_∞ will be the nearest stable fixed point, either above or below.
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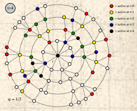
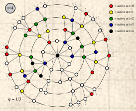
- Important: Actual form of G depends on ϕ_0.
- So choice of ϕ_0 dictates both G and starting point—can't start anywhere for a given G.

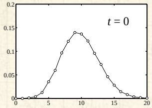


Outline



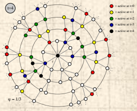
Early adopters—degree distributions

$t = 0$



$P_{k,t}$ versus k

Unpublished?



Early adopters—degree distributions

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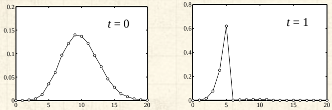
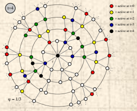


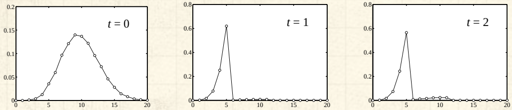


$P_{k,t}$ versus k

Unpublished?

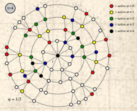
Early adopters—degree distributions

$t = 0$ $\quad$ $t = 1$ $\quad$ $t = 2$



$P_{k,t}$ versus k

Unpublished?



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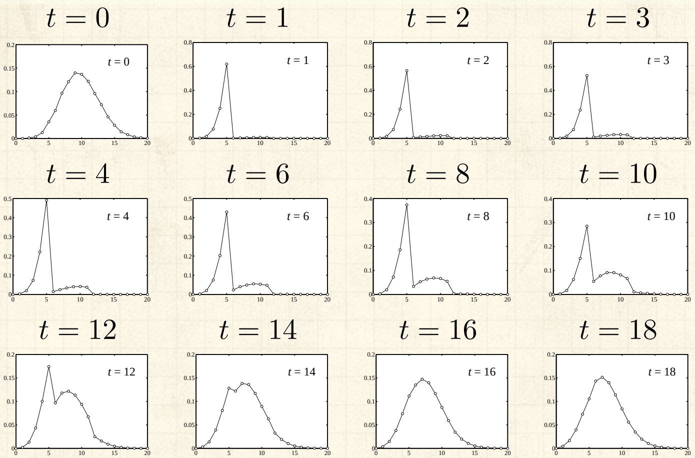

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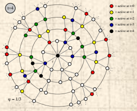
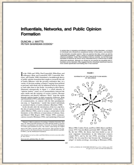
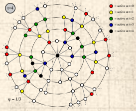



Influentials, Networks, and Public Opinion Formation

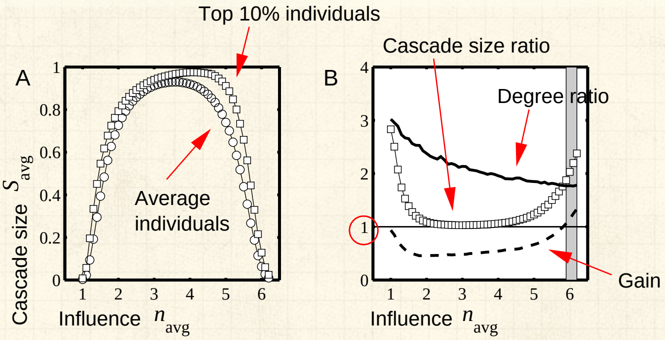
DUNCAN J. WATTS
PETER SHERIDAN DODDS

"Influentials, Networks, and Public Opinion Formation"
Watts and Dodds,
J. Consum. Res., **34**, 441–458, 2007. [27]

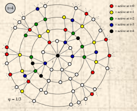
- Exploration of threshold model of social contagion on various networks.
- "Influentials" are limited in power.
- Connected groups of weakly influential-vulnerable" individuals are key.
- Average individuals can have more power than well connected ones.



The multiplier effect:



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



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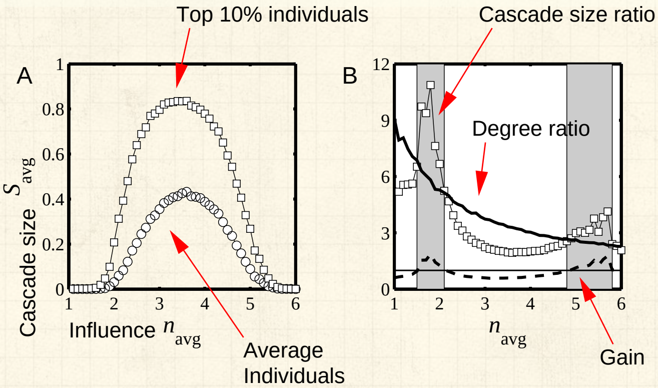
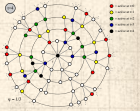
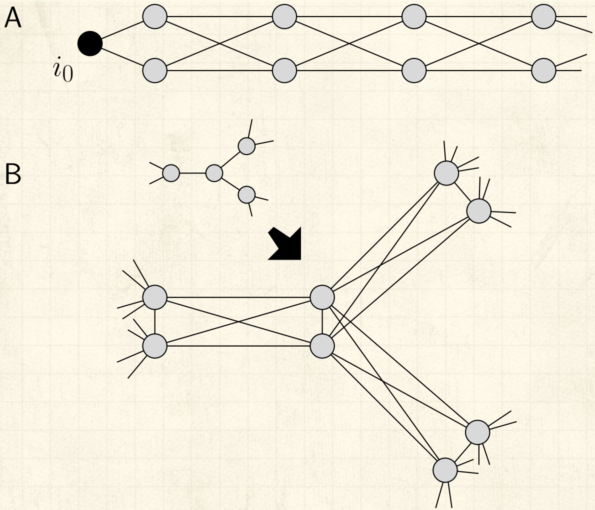


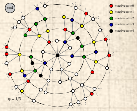
- Skewed influence distribution example.



Special subnetworks can act as triggers



$\phi = 1/3$ for all nodes



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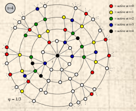
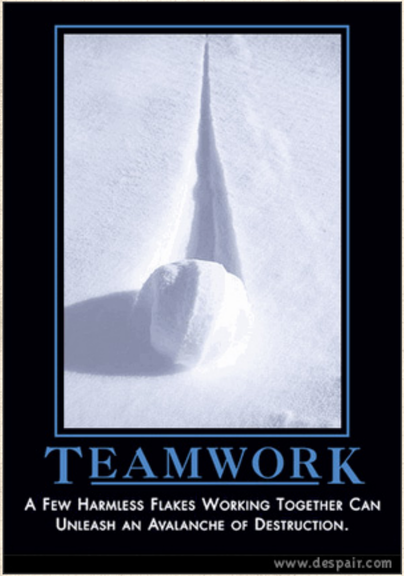
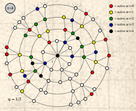


The power of groups...

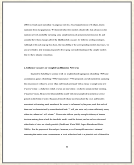


despair.com

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

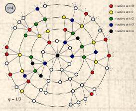


Extensions



"Threshold Models of Social Influence"
Watts and Dodds,
The Oxford Handbook of Analytical Sociology, **34**, 475–497, 2009. [28]

- Assumption of sparse interactions is good



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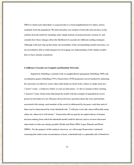

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- Assumption of sparse interactions is good
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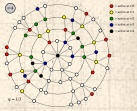

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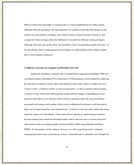

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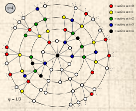

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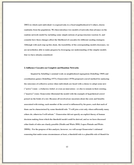

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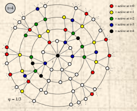
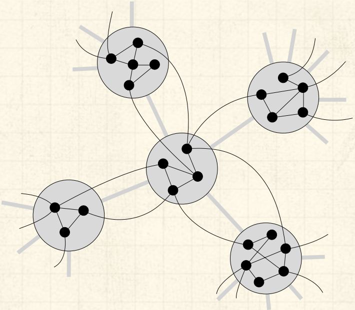
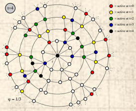
- Still, random networks don't represent all networks
- Major element missing: group structure



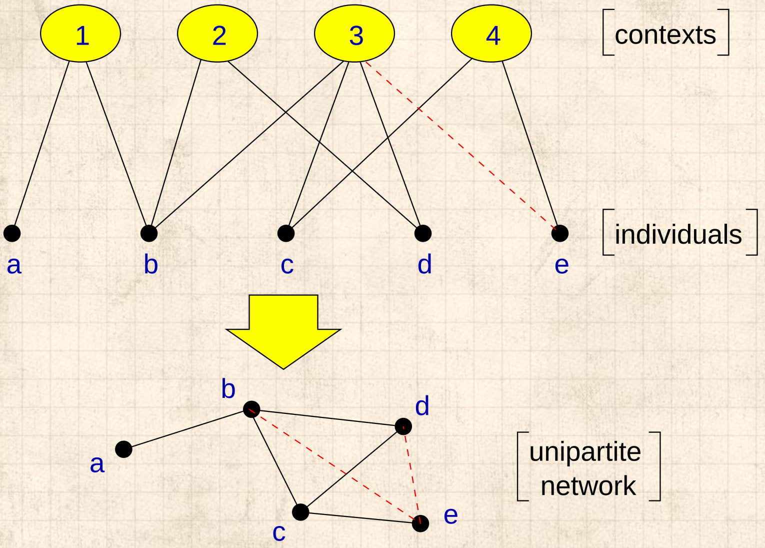
Group structure—Ramified random networks

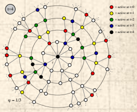


p = intergroup connection probability
q = intragroup connection probability.

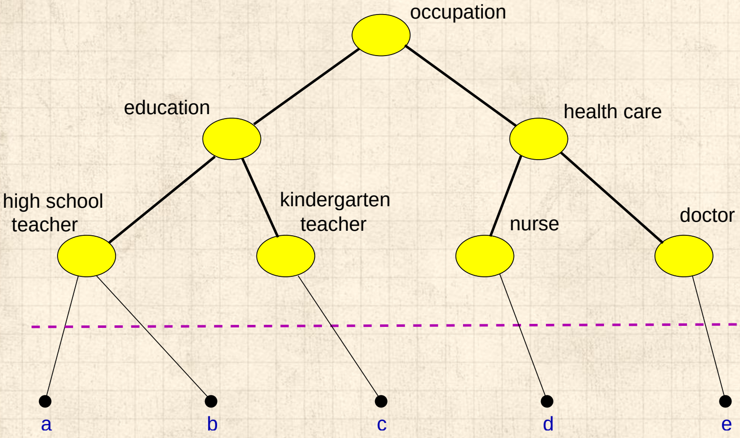


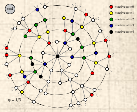
Bipartite networks



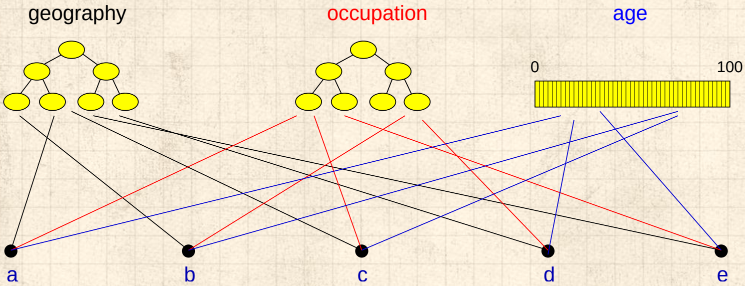


Context distance

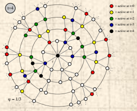




Generalized affiliation model

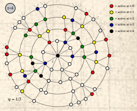


(Blau & Schwartz, Simmel, Breiger)



Generalized affiliation model networks with triadic closure

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



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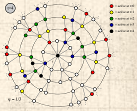

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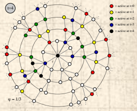
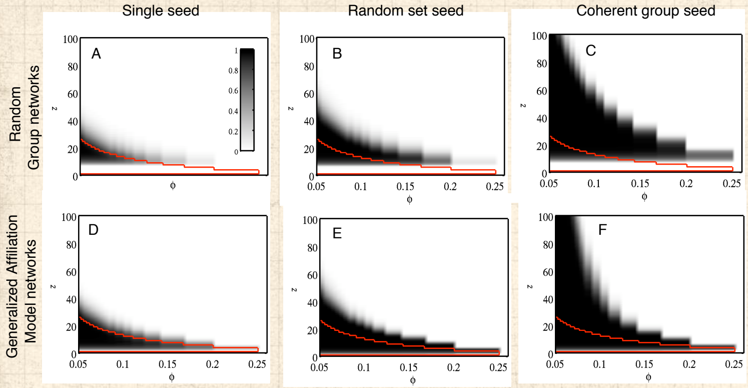
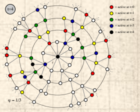
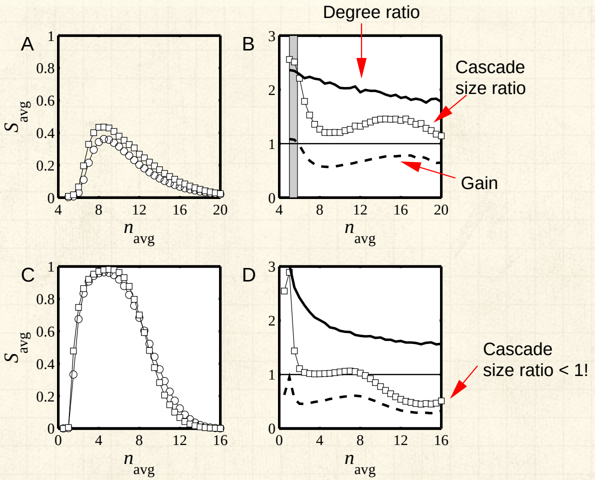


Cascade windows for group-based networks

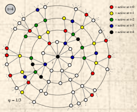




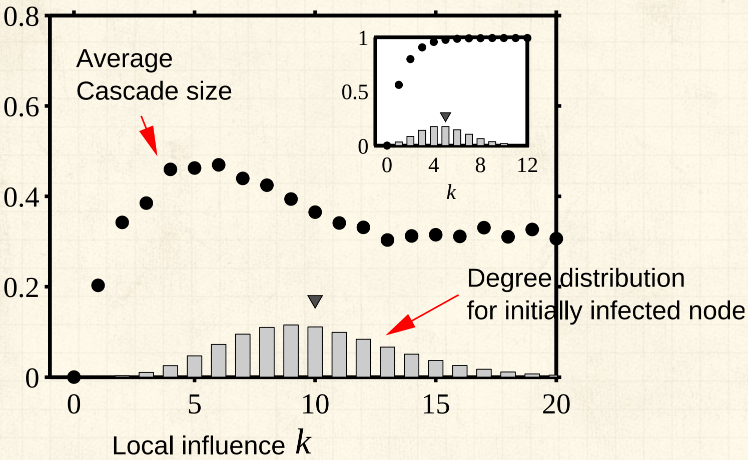
Multiplier effect for group-based networks:



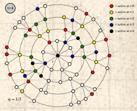
- Multiplier almost always below 1.



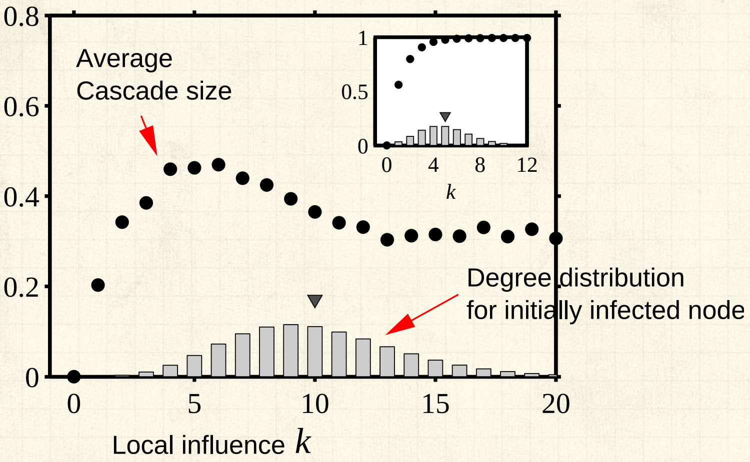
Assortativity in group-based networks

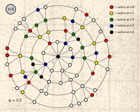


- The most connected nodes aren't always the most 'influential.'



Assortativity in group-based networks



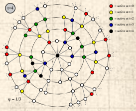


- The most connected nodes aren't always the most 'influential.'
- Degree assortativity is the reason.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.



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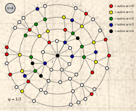

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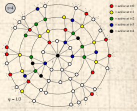

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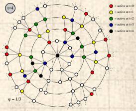

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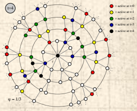

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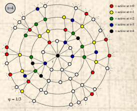

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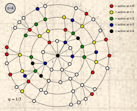

Social contagion

Implications

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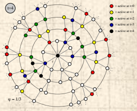
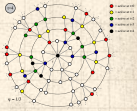


Social contagion

Implications

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



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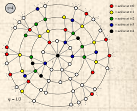
  (Idea of opinion leaders spreads well...)



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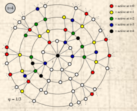

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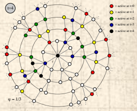

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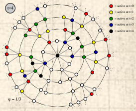

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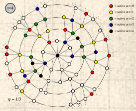
- Entities can be novel or designed to combine with others, e.g. block another one.

Spreading and unspreading: Empires

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



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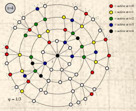

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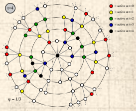

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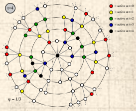

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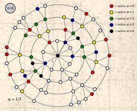

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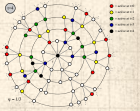

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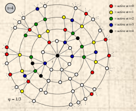

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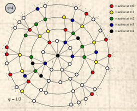

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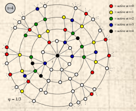

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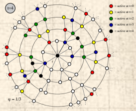

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