Syllabus: Complex Social Systems

A guided exploration of concepts and methods

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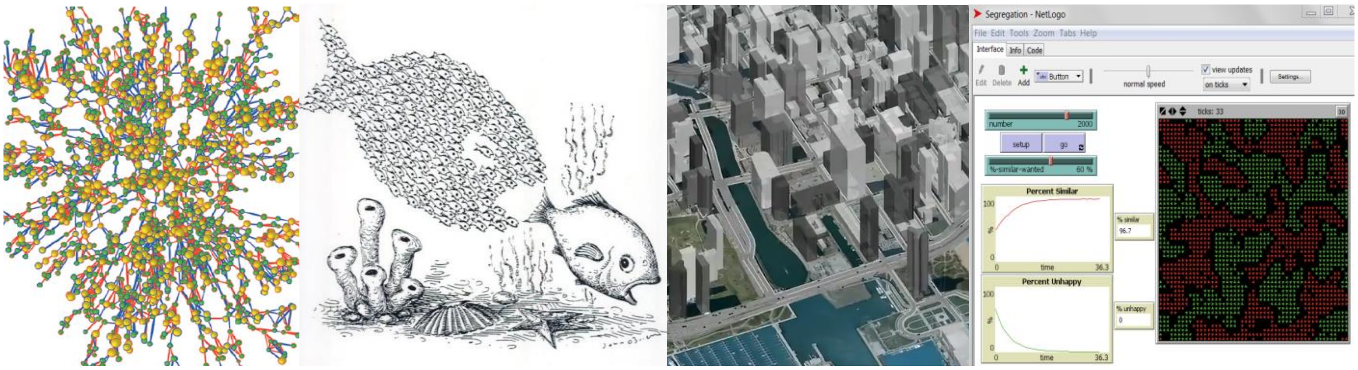

Complex systems are systems composed of interdependent entities that as a whole exhibit properties and behaviors not obvious from the sum of its individual parts, as the involved entities constantly react to the patterns they create themselves. From the invisible hand of Adam Smith and the creation of Rousseau's general will, to revolutionary uprisings and state-of-the-art digital social networks, society is full of complexities. We discuss several of the new theories and practical tools that have been developed to study the ***emergence*** of ***non-linear macro patterns*** that arise out of a multiplicity of ***dynamical micro interactions***. We visit theoretical aspects, such as ***information theory***, ***computational complexity***, ***dynamical systems theory,*** and ***chaos theory*** (setting the limits of complex systems between order and randomness), as well as practical hands-on tools to tackle complexity, such as ***dynamical social network analysis***, ***big data webscraping, multi-level evolutionary analysis***, and ***agent-based modeling*** (computer simulations of social systems). We review a diverse set of analytical and numerical methods and also play around with diverse software tools to explore emergent phenomena in complex social systems in action. No prerequisites are necessary to participate in the course.

Course Outline (sessions of 2.5 - 3 hours each)

(1) Overview: What are complex systems?

Complex systems are composed of agents that are connected, interdependent, diverse, adaptive, and path dependent, and whose interactions result in emergent phenomena. In this session we discuss these features, introduce some analytical tools and ask about implications for the social sciences.

Keywords (look up at: www.wikipedia.org): *Complex systems, Complex adaptive system; Chaos theory; Path dependence*.

Videos: What is Complexity Interviews (2min); What is Complexity? (5min); Complex Systems: an overview (4min); Complex systems science: a short film (part 2 of 4; 7min); Puppies! Now that I've got your attention, complexity theory (13min); Interactive Segregation (game).

(2) Social Network Analysis (part 1): analyzing the structure of networks

We begin with a review of one of the most developed branches of social complex systems science. Per definition, a society is a network of individuals, which makes the analysis of social network structure decisive. We discuss concepts and metrics of social networks, such as different measures of centrality, network partitioning into groups and clusters, homophily, transitivity, structural and regular equivalences, and the implications of weighted ties, among others. We will also start using software to analyze social networks in practice.

Keywords (look up at: www.wikipedia.org): *Social network analysis; Graph theory; Network theory; Social network*.

Videos: The hidden influence of social networks (18min); Strength of weak ties (3min); What Networks Can Tell Us about the World (71min).

Castells, M. (2011). Communication power. Oxford: Oxford University Press. p. 19-42.

Q: What is Castell's concept of the "Network Society"? How does it affect enterprises and States?

Hanneman, R., & Riddle, M. (n.d.). Introduction to social network methods. Riverside CA: University of California, Riverside. Retrieved from http://www.faculty.ucr.edu/~hanneman/nettext/ Ch. 1 & Ch. 10

Q: Q: Describe a network with 3 different kinds of "Scales of measurement" of relations. How do you expect the networks to be different?

Q: What are Degree Centrality, Closeness Centrality and Betweenness Centrality?

(3) Agent-based Models (part 1): computer simulations

Traditional analytical methods reach a limit when trying to understand non-linear emergent phenomena with an intermediate degree of interdependence. Computer simulations allow us to obtain numerical results that provide a basic understanding of emergent dynamics in many kinds of social systems. These models create artificial societies of different levels of sophistication. We experience the logic unfold in hands-on software simulations of such artificial societies.

Keywords (look up at: www.wikipedia.org): Agent-based model; artificial society; emergence.

Video Playlist: Why Agent-Based Modeling? (7min); Agent-based Crowd Simulation in Airports (3min); Mesolithic Society (4min); Simulating Emergency Room (3min); Real military simulation (4min); Laboratory simulation (2 min).

Rauch, J. (2002). Seeing Around Corners. The Atlantic, (April); http://www.theatlantic.com/magazine/archive/2002/04/seeing-around-corners/302471/

Q: Which of the "seeing around (non-linear) corners" insights is your favorite? Why?

Beinhocker, E. D. (2007). The Origin of wealth: evolution, complexity, and the radical remaking of economics. Boston: Harvard Business School. Chapter 4.

Q: Where does the Pareto distribution on Sugarscape come from?

Nowak, A., Rychwalska, A., & Borkowski, W. (2011). Why Simulate? To Develop a Mental Model. Journal of Artificial Societies and Social Simulation, 16(3), 12.

Yong, E. (2013). How the Science of Swarms Can Help Us Fight Cancer and Predict the Future. Wired Magazine, (Science). Retrieved from http://www.wired.com/wiredscience/?p=150947

Q: What is an example for how in swarms "the total is more than the sum of its parts"?

(4) Multilevel Evolution: what evolves?

In this session we revisit the theory of evolution and analyze the differences between biological- and social evolution. Social systems evolve at different levels, while interactions at a lower (micro) levels lead to emergent patterns on higher (macro) levels. We review some of the arising paradoxes (such as social altruism among selfishly evolving individuals) and review an analytical method that allows us to analyze the evolution at various levels (the Price equation).

Keywords (look up at: www.wikipedia.org): Evolution; Natural Selection; Price equation; Fisher's fundamental theorem of natural selection.

Videos: How evolution works (3 min); Claude Shannon: father of the information age (29 min).

Frank, S. A. (2012). Natural selection. IV. The Price equation. Journal of Evolutionary Biology, 25(6), 1002–1019. http://stevefrank.org/reprints-pdf/12NS04.pdf

Q: What does the Price equation do? What is the difference between natural selection and evolution?

Frank, S. A. (2012). Natural selection. V. How to read the fundamental equations of evolutionary change in terms of information theory. Journal of evolutionary biology, 25(12), 2377–96. http://stevefrank.org/reprints-pdf/12NS05.pdf

Q: How does Frank interpret natural selection in terms of Fisher Information?

Hilbert, M (2013); Linking Information, Knowledge and Evolutionary Growth: A multilevel interplay between natural selection and informed intervention; forthcoming.

: What's the relation between Shannon information, Kolmogorov Complexity and evolutionary growth?

(5) Between Chance and Order: between Shannon entropy and Kolmogorov complexity

Results from information theory and computer science have shown that information is a physical thing that is closely related to the ability to extract energy. Just as the nimble-fingered Maxwell's demon uses information to do work, so do social systems convert information into knowledge, and both into fitness. We review how social systems process information to grow.

Keywords (look up at: www.wikipedia.org): Entropy (information theory); Kolmogorov complexity; Maxwell's demon.

Videos: Maxwell's Demon and the Nature of Information (12 min); Maxwell's Demon and Perpetuum Mobile of second kind (3min); Journey into Information Theory.

Gell-Mann, M., & Lloyd, S. (1996). Information measures, effective complexity, and total information. Complexity, 2(1), 44–52.

: What is Gell-Mann and Lloyd's effective complexity?

Supplementary Appendix, PART B of Hilbert, M (2013); Linking Information, Knowledge and Evolutionary Growth: A multilevel interplay between natural selection and informed intervention; forthcoming.

: Discuss how the following concepts matter for the relation between Shannon information and Kolmogorov Complexity: probabilistic, deterministic, asymptotically equivalent

Zurek, W. H. (1998). Algorithmic randomness, physical entropy, measurements, and the Demon of Choice. http://arxiv.org/abs/quant-ph/9807007

: What is Zurek's physical entropy?

(6) Big Data: real-time digital footprints of complex social systems

The digital age changes the way in which data is produced and collected. With over 99% of all information available in digital format, and with a mobile penetration of 98% worldwide, the paradigm of Big Data allows in many cases to give sample (n = N = all) and get cheap proxies in real time for many key indicators of complex social dynamics. That applies from communication patterns, to the level of happiness of a society.

Keywords (look up at: www.wikipedia.org): Big Data; Predictive Analytics.

Videos: What is Big Data (4min); Cukier TED on Big Data (15min); More Cukier on Big Data (8min); Visualizing Twitter data (6min); Big Data history & CERN (6min); Helbing on digital Crystal Balls (48min).

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: a revolution that will transform how we live, work and think*. London: John Murray; http://books.google.cl/books?id=HpHcGAkFEjkC .

: What are the characteristics of Big Data according to the authors? Pick your favorite case example and elaborate what you like so much about it.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *Big data: The next frontier for innovation, competition, and productivity. McKinsey & Company*. http://www.mckinsey.com/Insights/MGI/Research/Technology_and_Innovation/Big_data_The_next_frontier_for_innovation

: What are the characteristics of Big Data according to these authors? Pick your favorite case example and elaborate what you like so much about it.

(7) **Diversity:** aggregate models vs. agent-based diversity

Complex systems are made of diverse entities. Many of the mainstream aggregate models average or simplify this diversity, which works impressively well in some cases, but fails terribly in others. We discuss the main concepts to understand diversity. We review several examples of how diversity provides robustness and efficiency in social dynamics on the micro- and macro levels.

Keywords (look up at: www.wikipedia.org): Entropy, Diversity, Variance.

Videos: Diversity Prediction Theorem (28min); The power of diversity (60 min); Global Product Space (18 min); Building Blocks of Economic Complexity (4 min).

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Chung, S., Jimenez, J., … Yildirim, M. A. (2011). The atlas of economic complexity: mapping paths to prosperity. Harvard University Center for International Development, MIT Media Lab. http://atlas.media.mit.edu/book

: What is “economic complexity” according to the authors? Do you agree that this is “complexity”?

(8) **Social Network Analysis (part 2):** growing dynamic networks to make predictions

We review methods that allow us to test the validity of network models, such as Erdos-Renyi-, small world-, and preferential attachment networks. We also examine how we can grow dynamic social networks to make predictions in areas such as the spread of epidemics, innovations and ideas. Last but not least, we discuss the relation between network structure and function, and inspect how social networks can be optimized with regard to the tradeoff between efficiency and robustness.

Keywords (look up at: www.wikipedia.org): Erdos–Rényi model, ERGM, Diffusion of innovations, Percolation theory, epidemic model.

Videos: Using Networks to Make Predictions (70min); Network Theory: Conceptual and Methodological Issues (60min); Diffusion of Innovations: Part1; Part2; Part3.

Newman, M. E. J. (2003). The Structure and Function of Complex Networks. SIAM REVIEW, 45, 167–256. http://www-personal.umich.edu/~mejn/courses/2004/cscs535/review.pdf

Q: What are random graphs and what are exponential random graphs?

Q: What is a small world network?

Q: Explain one model of network growth

(9) Agent-based Models (part 2): generative social science

The generativist motto of computer generated social science is: "If you didn't grow it, you didn't explain it!" We discuss the implications and limits of the new science of artificial societies. We also review new developments, such as the marriage of computer simulations with "Big (social) Data".

Keywords (look up at: www.wikipedia.org): Big Data, Simcity, induction, deduction.

Video Playlist: Prey Predator (2min); ABM in SecondLife (6min); How industry simulation software works (5min); Industrial Experimentation (3 min); People Animation (1 min); Programming with NetLogo (12min); Portland Simulation (28min).

Barrett, C. L., Eubank, S. G., & Smith, J. P. (2005). If Smallpox Strikes Portland... Scientific American, 292(3), 54–61. http://www.scientificamerican.com/article.cfm?id=if-smallpox-strikes-portl

Q: Describe a (hypothetical) example of how social Big Data and Agent-Based Models could be combined?

Epstein, J. M. (2005). Remarks on the Foundations of Agent-Based Generative Social Science. Santa Fe Institute Working Papers. http://www.santafe.edu/media/workingpapers/05-06-024.pdf

Q: Explain and elaborate on one of Epstein's 5 arguments about ABMs.

Helbing, D., & Balietti, S. (2011). How to Do Agent-Based Simulations in the Future: From Modeling Social Mechanisms to Emergent Phenomena and Interactive Systems Design (SFI Working Papers). Santa Fe Institute. http://www.santafe.edu/media/workingpapers/11-06-024.pdf

Q: Elaborate on your favorite argument / insight from the paper.

(10) Power-laws: omnipresent signature of complex systems?

Many social phenomena follow a long-tailed power-law, instead of a normal Bell curve. The unique properties of scale-free power-laws differ significantly from those of the traditional normal distribution. This has implications for understanding and intervening in manifold social dynamics. We discuss several of the fascinating generative mechanisms of power-laws, such as self-organized criticality, highly optimized tolerance, allometric scaling, and positive feedback. We also take a critical look at the authenticity of many supposed power-laws.

Keywords (look up at: www.wikipedia.org): Power-law; Pareto distribution, Zipf law; allometry, factals.

Videos: An Illustration of Self-Organized Criticality (25min); The surprising math of cities and corporations (17min); Cities are like stars (3 min); Cities and scientific productivity (28 min); Fractals in nature (3min) .

Gladwell, M. (2006, February 13). Million-Dollar Murray, Dept. of Social Services. Retrieved from http://www.gladwell.com/2006/2006_02_13_a_murray.html

: *What makes power-laws socially as relevant?*

Adamic, L. (2000). Zipf, Power-law, Pareto - a ranking tutorial. Research at HP Labs : Information Dynamics Lab. http://www.hpl.hp.com/research/idl/papers/ranking/

: *What is the difference between the Zipf law, power-law, and Pareto law?*

Newman, M. (2005). Power laws, Pareto distributions and Zipf's law. Contemporary Physics, 46(5), 323. http://www-personal.umich.edu/~mejn/courses/2006/cmplxsys899/powerlaws.pdf

: *What is self-organized criticality and what is highly optimized tolerance?*

(11) Review and summary discussion

Basic texts

Castells, M. (2005). *The Network Society: from Knowledge to Policy*. Center for Transatlantic Relations.

Epstein, J. M., & Axtell, R. L. (1996). *Growing Artificial Societies: Social Science from the Bottom Up*. A Bradford Book.

Frank, S. A. (1998). *Foundations of Social Evolution*. Princeton University Press.

Gell-Mann, M. (1995). *The Quark and the Jaguar: Adventures in the Simple and the Complex*. NY: St. Martin's Griffin.

Gell-Mann, M., & Lloyd, S. (1996). Information measures, effective complexity, and total information. *Complexity*, 2(1), 44–52.

Hausmann, R., Hidalgo, C. A., et al., (2011). *The atlas of economic complexity*: mapping paths to prosperity. Harvard University Center for International Development, MIT Media Lab.

Mitchell, M. (2011). *Complexity: A Guided Tour*. Oxford University Press, USA.

Monge, P. R., & Contractor, N. (2003). *Theories of Communication Networks*. Oxford University Press.

Newman, M. (2010). *Networks: An Introduction*. New York: Oxford University Press, USA.

Page, S. (2009). *Understanding Complexity*. The Great Courses, Course No. 5181, Virginia.

Schelling, T. C. (2006). *Micromotives and Macrobehavior*. W. W. Norton & Company.

About the instructor

Martin Hilbert pursues a multidisciplinary approach to understanding the role of information, communication and knowledge in the development of complex social systems. He holds doctorates in Communication, and in Economics and Social Sciences, and a permanent appointment as Economic Affairs Officer of the United Nations. His work has been published in recognized academic journals such as *Science, Psychological Bulletin, World Development,* and *Technological Forecasting and Social Change,* and has been featured in popular magazines such as *Scientific American, The Economist, The Wall Street Journal, Wired, Washington Post, BBC, Die Welt, Correio Braziliense, La Repubblica,* among others. He has provided technical assistance to Heads of State, government experts, legislators, diplomats, companies and civil society organizations in over 20 countries. More in: http://www.martinhilbert.net