lecture 16: multilevel organization of complex systems II

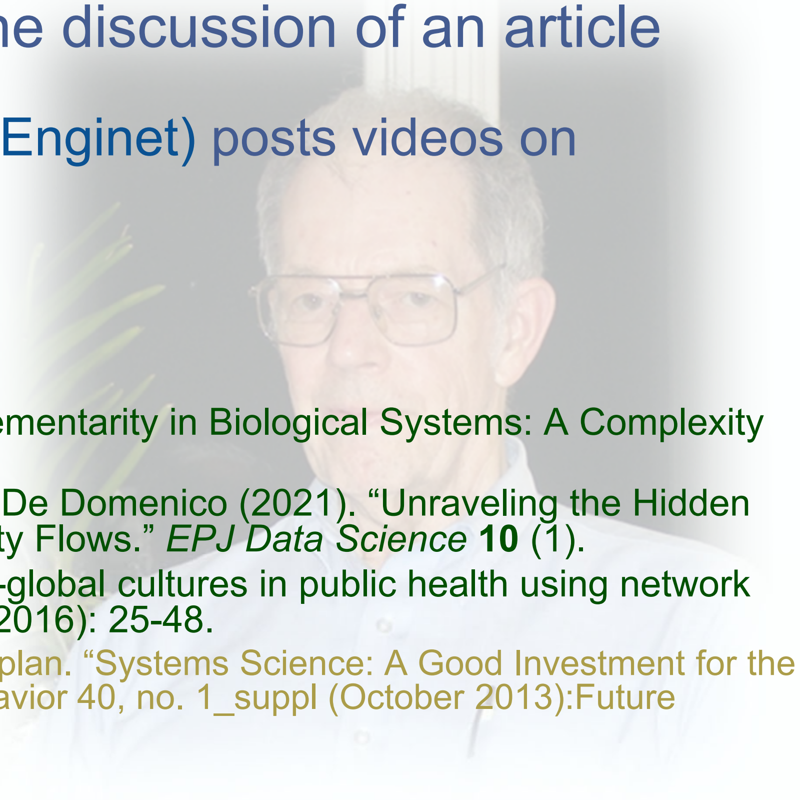
Multilevel Organization of Complex Systems

evaluation

- Participation: 20%.
  - class discussion, everybody reads and discusses every paper
  - engagement in class, including online
- Paper Presentation and Discussion: 20%
  - All students are assigned to a Reading and Discussion Group
  - **SSIE501** students in group present and discuss papers
    - all students are supposed to read and participate in discussion of every paper.
    - *section 01 groups* present in class, *section 20 groups* present via zoom or send a video
  - Presenter group prepares short summary of assigned paper (15 minutes)
    - no formal presentations or PowerPoint unless figures are indispensable.
  - Summary should:
    - 1) Identify the key goals of the paper (not go in detail over every section)
    - 2) What discussant liked and did not like
    - 3) What authors achieved and did not
    - 4) Any other relevant connections to other class readings and beyond.
  - **ISE440** students in group participate as lead discussants
    - not to present the paper, but to comment on points 2-3) above
  - Class discussion is opened to all
    - lead discussant ensures important paper contributions and failures are addressed
  - Post presentation 1-2 page report uploaded to Brightspace
    - 1-4) plus 5) statement of individual contributions
- Black Box: 60%
  - Group Project (2 parts)
    - Assignment I (25%) and Assignment II (35%)

rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

more upcoming readings (check brightspace)



- Paper Presentation: 20%
  - Present (501) and lead (501&440) the discussion of an article related to the class materials
  - *section 01* presents in class, *section 20* (Enginet) posts videos on Brightspace (exceptions possible)
- Module 4 – Multi-level complexity
  - November 16th / 28th ?
    - Reading and Discussion Group 5 (Enginet)
      - Theise, N.D., and M.C. Kafatos. [2013]. "Complementarity in Biological Systems: A Complexity View." *Complexity* **18** (6): 11-20.
      - Gallotti, Riccardo, Giulia Bertagnolli, and Manlio De Domenico (2021). “Unraveling the Hidden Organisation of Urban Systems and Their Mobility Flows.” *EPJ Data Science* **10** (1).
      - Pescosolido, Bernice A., et al. "Linking genes-to-global cultures in public health using network science." *Handbook of applied system science* (2016): 25-48.
        - Optional: Mabry, Patricia L., and Robert M. Kaplan. “Systems Science: A Good Investment for the Public’s Health.” Health Education & Behavior 40, no. 1_suppl (October 2013):Future Modules
  - See brightspace

more upcoming readings (check brightspace)

- Paper Presentation: 20%
  - Present (501) and lead (501&440) the discussion of an article related to the class materials
  - *section 01* presents in class, *section 20* (Enginet) posts videos on Brightspace (exceptions possible)
- Module 4 – Multi-level complexity
  - November 28th ?
    - Reading and Discussion Group 1
      - Prieto-Curiel, et al [2023]. “Reducing Cartel Recruitment Is the Only Way to Lower Violence in Mexico.” *Science* **381** (6664): 1312–16.
        - Optional: Caulkins, Jonathan P., Beau Kilmer, and Peter Reuter [2023]. “Modeling Cartel Size to Inform Violence Reduction in Mexico.” *Science* **381**, no. 6664: 1291–93.
    - Reading and Discussion Group 2
      - Gan, Xiao et al. [2023] “Network Medicine Framework Reveals Generic Herb-Symptom Effectiveness of Traditional Chinese Medicine.” *Science Advances* **9**, (43): eadh0215
- Module 5 – Interdisciplinarity
  - November 30th ?
    - Reading and Discussion Group 3
      - Wu, L., Wang, D., & Evans, J. A. [2019].”Large teams develop and small teams disrupt science and technology”. *Nature* **566**: 378–382
    - Reading and Discussion Group 4
      - Trochim, William M et al [2006]. “Practical Challenges of Systems Thinking and Modeling in Public Health.” *American Journal of Public Health* **96**(3): 538–46.
        - Optional: Rusoja, Evan, et al [2018]. “Thinking about Complexity in Health: A Systematic Review of the Key Systems Thinking and Complexity Ideas in Health.” *Journal of Evaluation in Clinical Practice* **24** (3): 600–6
    - Reading and Discussion Group 5
      - Editorial. (2015). Mind meld. *Nature*, **525**(7569), 289–90.
      - Van Noorden, R. (2015). Interdisciplinary research by the numbers. *Nature*, **525**(7569), 306–7.
      - Ledford, H. (2015). How to solve the world’s biggest problems. *Nature*, **525**(7569), 308–11.
        - Optional: Kaushal, A., & Altman, R. B. (2019). “Wiring minds”. *Nature*, **576**(7787), S62-S63.
        - Optional: Iwasaki, A. (2019) “Why we need to increase diversity in the immunology research community”. *Nat Immunol* **20**, 1085–1088.
    - See brightspace

Questions and suggestions

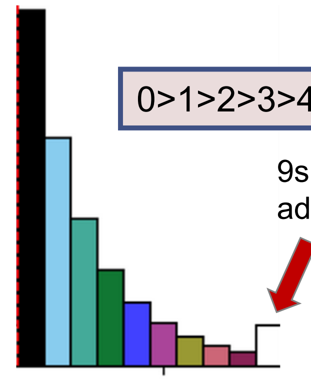
- Remember “published” facts
  - Odd/Even behavior in Q1
  - Statistical behavior in Q2
  - Different regions, transition sequence, complexity in Q4
- Collect or request data (cite)
- Are there quadrant dependencies?
- Focus on smaller grid (mask) subsets?
- Think of neighborhoods and boundary conditions
- **Move from descriptive to mechanistic models**
- Induction and deduction
  - Data and reasoning
  - Given a model, are things you have never seen possible?

$$state(cell(i,j))_{t+1} = ?_t \otimes ?.....$$

Q1

1. $0 \rightarrow 0$
2. $\{5\} \rightarrow \{0, 5\}$
3. $\{2, 4, 6, 8\} \rightarrow \{0, 2, 4, 6, 8\}$
4. $\{1, 3, 7, 9\} \rightarrow \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

Q2



0>1>2>3>4>5>6>7>8 >? 9

9s seem to have a slight advantage in prevalence ?

Q3 **Q4**

Are inner regions the same?

$\rightarrow 0$
$\rightarrow 3$
$\rightarrow 6$
$\rightarrow 9$

Inner region model

$0 \rightarrow 3 \rightarrow 9 \rightarrow 6 \rightarrow 0$

Outer region model

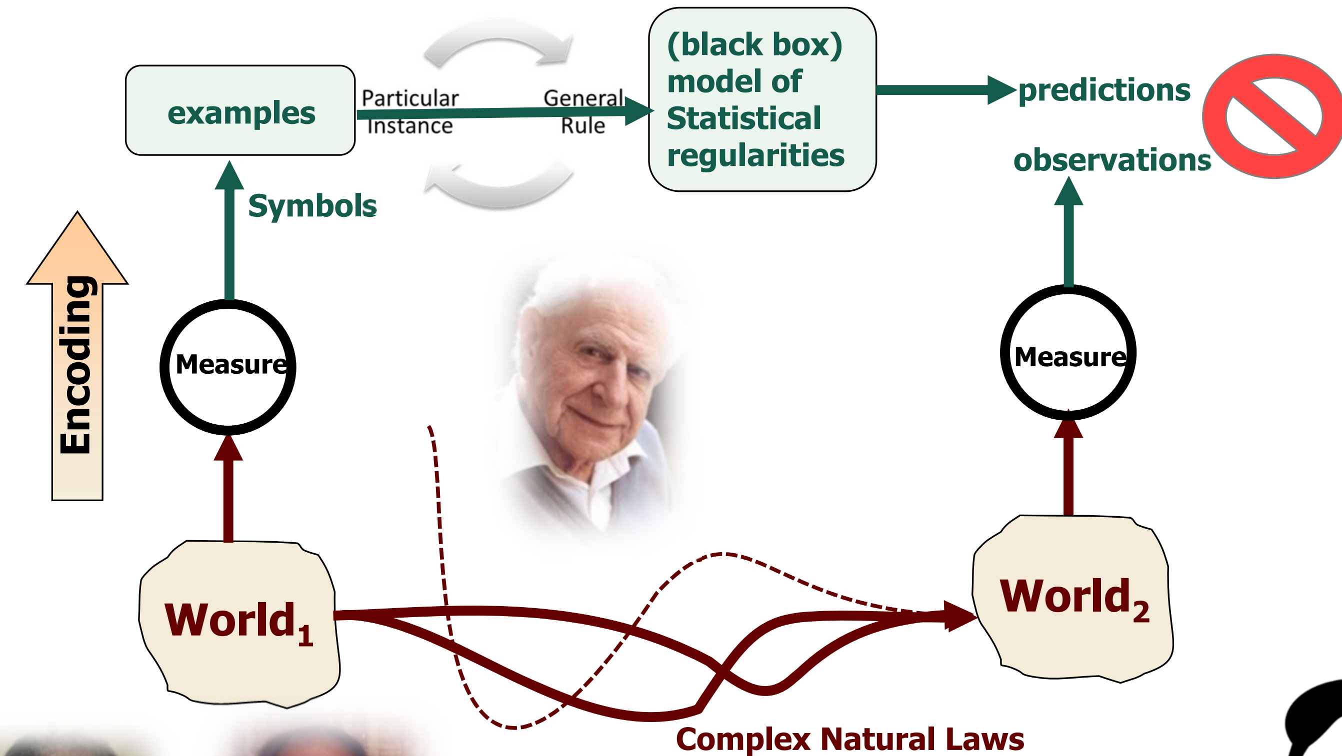
$\rightarrow 0$
$\rightarrow 9$

?

0 $\rightarrow$ **3,9**
1,2 $\rightarrow$ **0,3,9**
3,4,5 $\rightarrow$ **0,6,9**
6,7,8 $\rightarrow$ **0,3,9**
9 $\rightarrow$ **0,6**

BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

inductive models can be falsified but cannot predict black swans



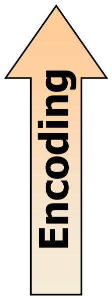

Nassim Nicholas Taleb

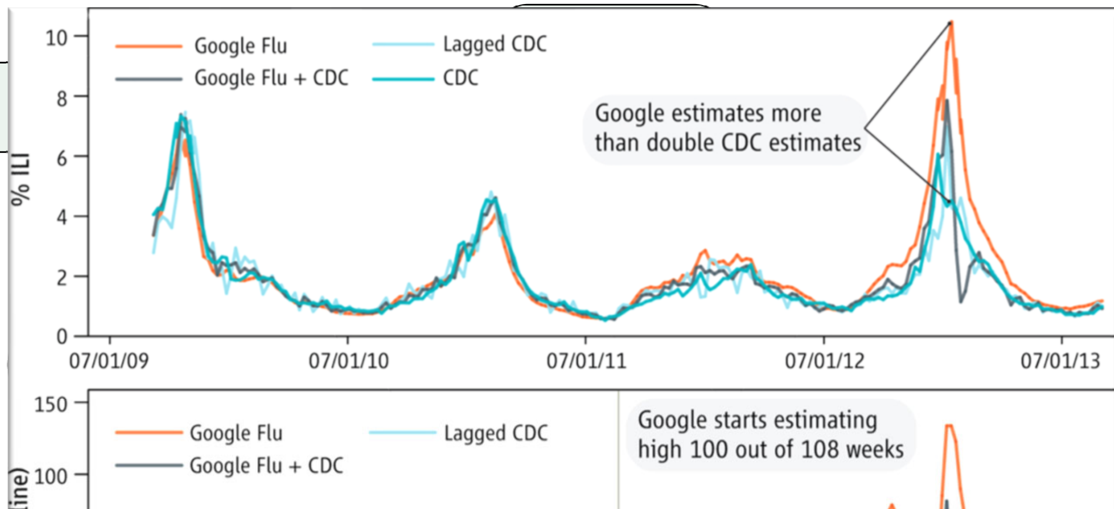

Howard Pattee


Robert Rosen

BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

inductive models can be falsified but cannot predict black swans

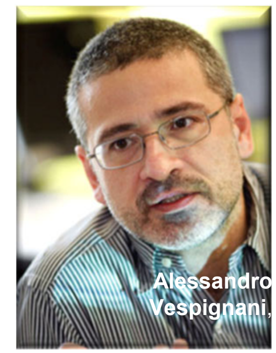




The Parable of Google Flu: Traps in Big Data Analysis

David Lazer[1,2,*], Ryan Kennedy[1,3,4], Gary King[3], Alessandro Vespignani[5,6,3]
+ See all authors and affiliations

Science 14 Mar 2014:
Vol. 343, Issue 6176, pp. 1203-1205
DOI: 10.1126/science.1248506




Nassim Nicholas Taleb


Howard Pattee


Robert Rosen

How is the DDI phenomenon in human populations?

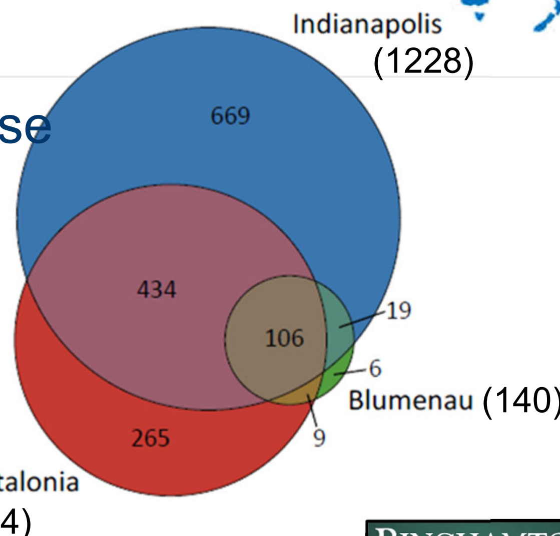
Comparing 3 distinct health systems

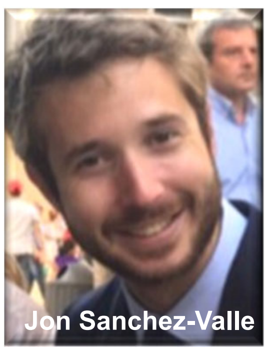
Indianapolis (private)
1,228 unique *DrugBank* IDs dispensed to **264,607** patients during **2 years** (Jan 2017–Dec 2018).

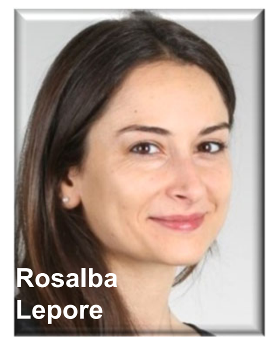
Blumenau (public, free)
140 unique *DrugBank* IDs dispensed to **133,047** patients during **18 months** (Jan 2014–Jun 2015).

Catalonia
814 unique *DrugBank* IDs administered to **5,555,924** patients during **11 years** (Jan 2008-Dec 2018).

drug universe

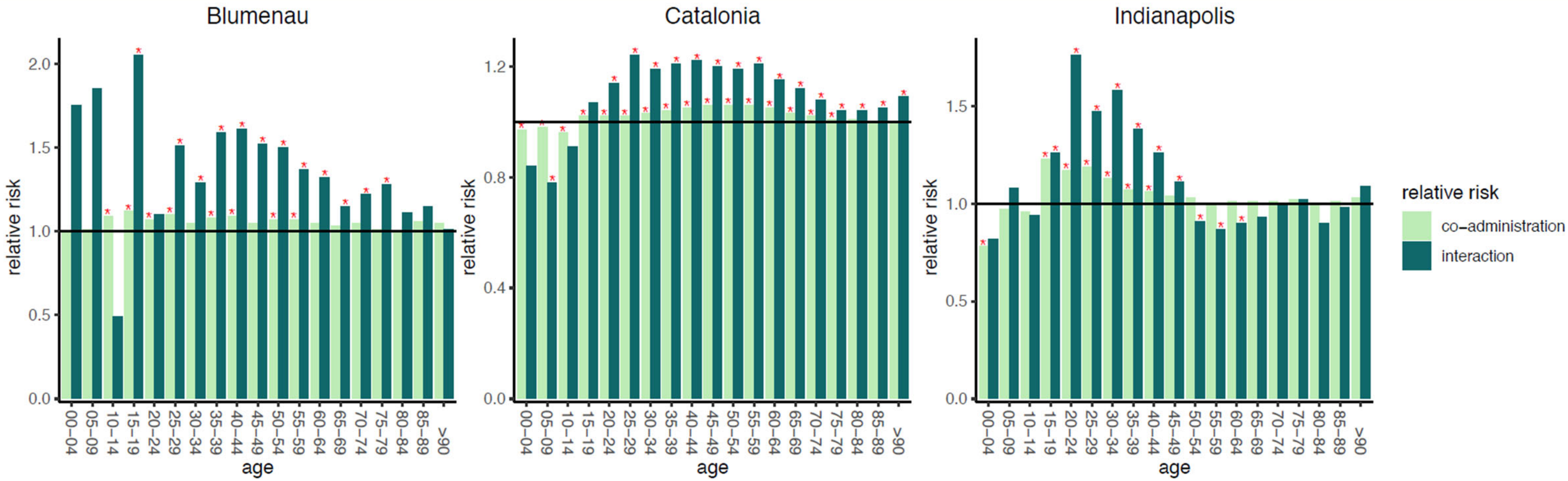






Sanchez-Valle et al [2023]. *medRxiv* 2023.02.06.23285566,
Correia, Araujo, Mattos, Wild & Rocha [2019]. *NPJ Digital Medicine*. 2:74.

gender and age biases in drug-drug interactions



Indianapolis (private)
1,228 unique *DrugBank* IDs dispensed to **264,607** patients during **2 years** (Jan 2017–Dec 2018).

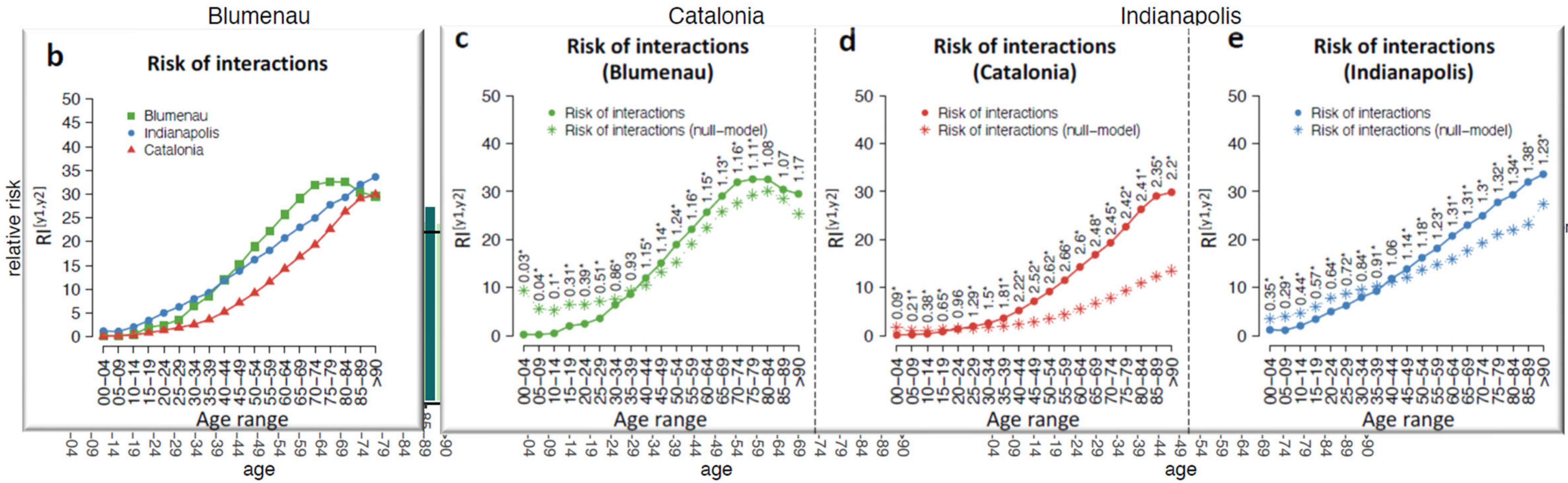
Blumenau (public, free)
140 unique *DrugBank* IDs dispensed to **133,047** patients during **18 months** (Jan 2014–Jun 2015).

Catalonia
814 unique *DrugBank* IDs administered to **5,555,924** patients during **11 years** (Jan 2008-Dec 2018).

Sanchez-Valle et al [2023]. *medRxiv* 2023.02.06.23285566,

BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

gender and age biases in drug-drug interactions



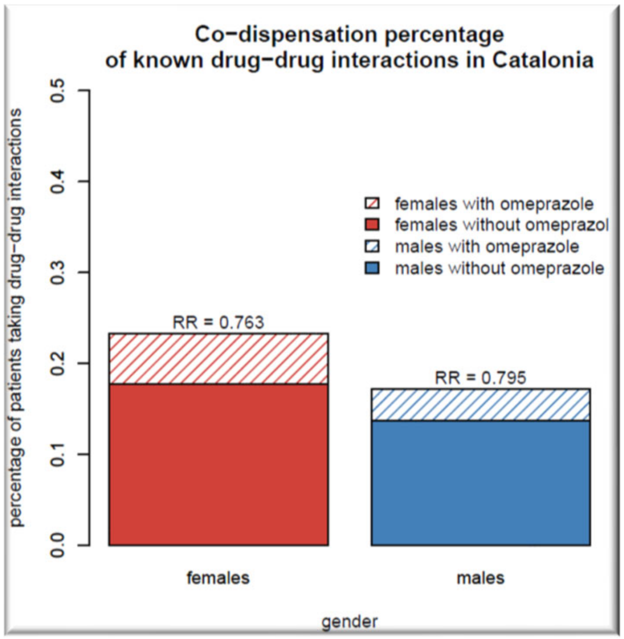
Indianapolis (private)
1,228 unique *DrugBank* IDs dispensed to **264,607** patients during **2 years** (Jan 2017–Dec 2018).

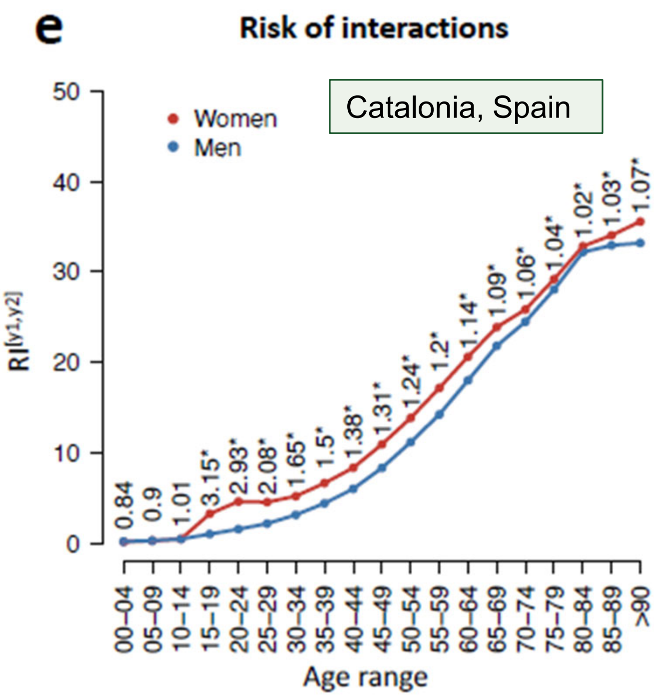
Blumenau (public, free)
140 unique *DrugBank* IDs dispensed to **133,047** patients during **18 months** (Jan 2014–Jun 2015).

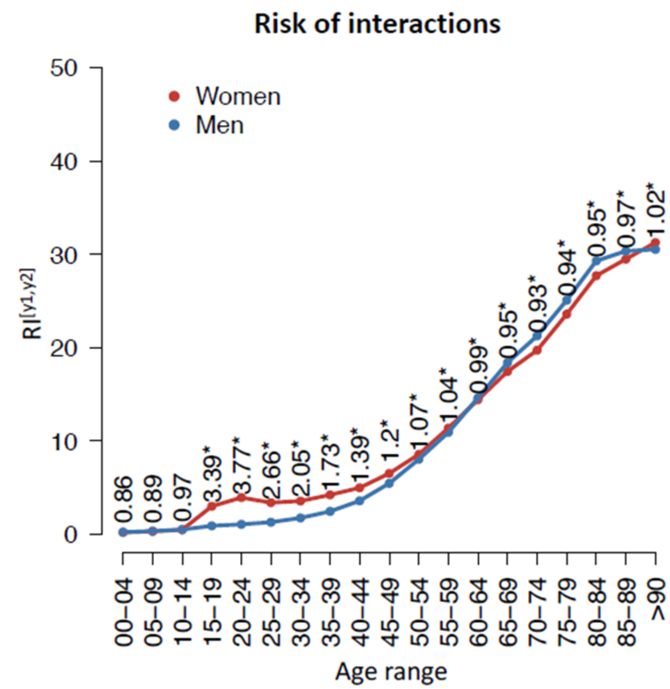
Catalonia
814 unique *DrugBank* IDs administered to **5,555,924** patients during **11 years** (Jan 2008-Dec 2018).

Sanchez-Valle et al [2023]. *medRxiv* 2023.02.06.23285566,

gender and age biases in drug-drug interactions





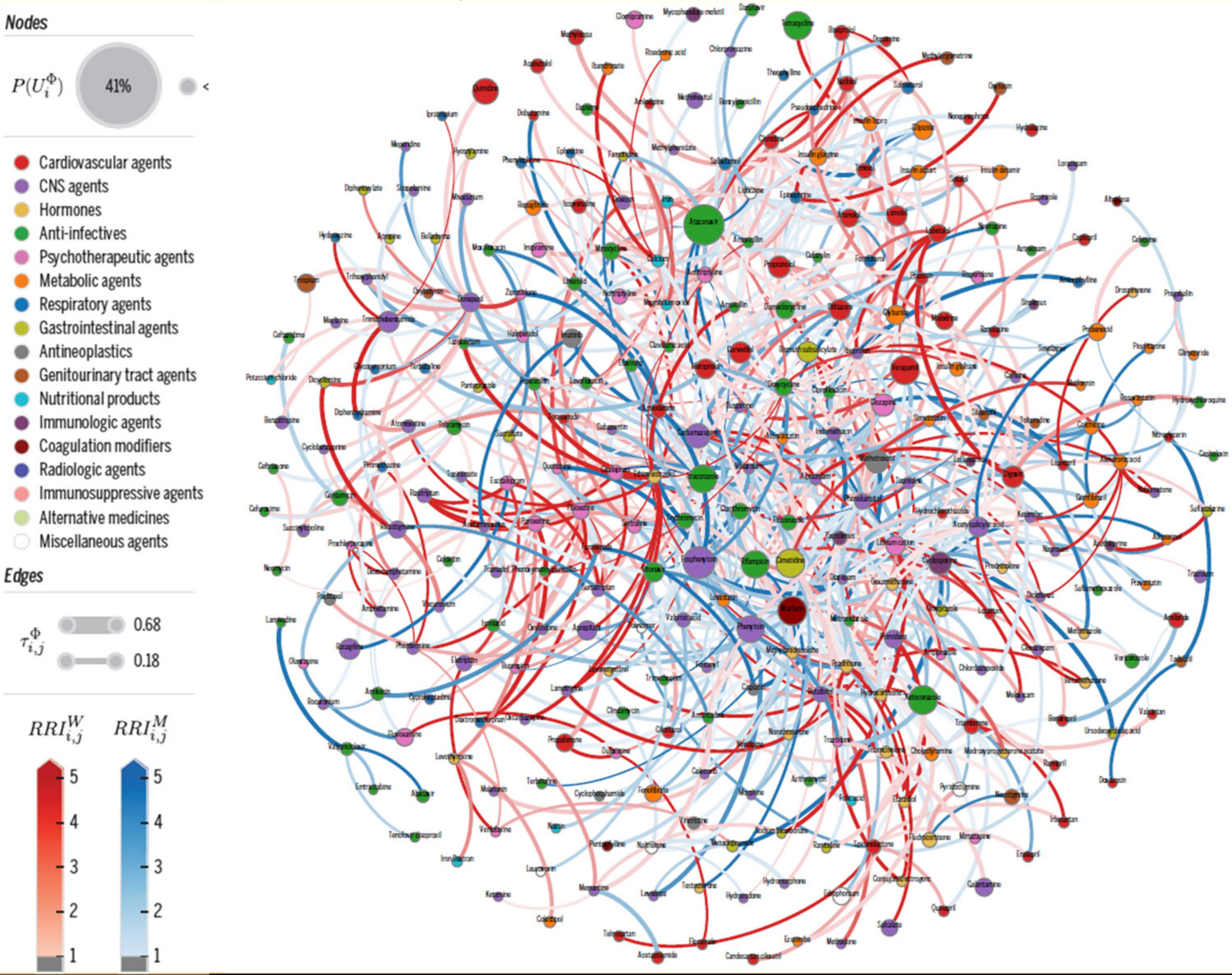


what actionable interventions?

Sanchez-Valle et al [2023]. *medRxiv* 2023.02.06.23285566,

How is the DDI phenomenon in human populations?

Browsable networks to synthesize information and aid actionable interventions



Catalonia
814 unique *DrugBank* IDs administered to **5,555,924** patients during **11 years** (Jan 2008-Dec 2018).

Indianapolis
1,228 unique *DrugBank* IDs dispensed to **264,607** patients during **2 years** (Jan 2017–Dec 2018).

Blumenau
140 unique *DrugBank* IDs dispensed to **133,047** patients during **18 months** (Jan 2014–Jun 2015).

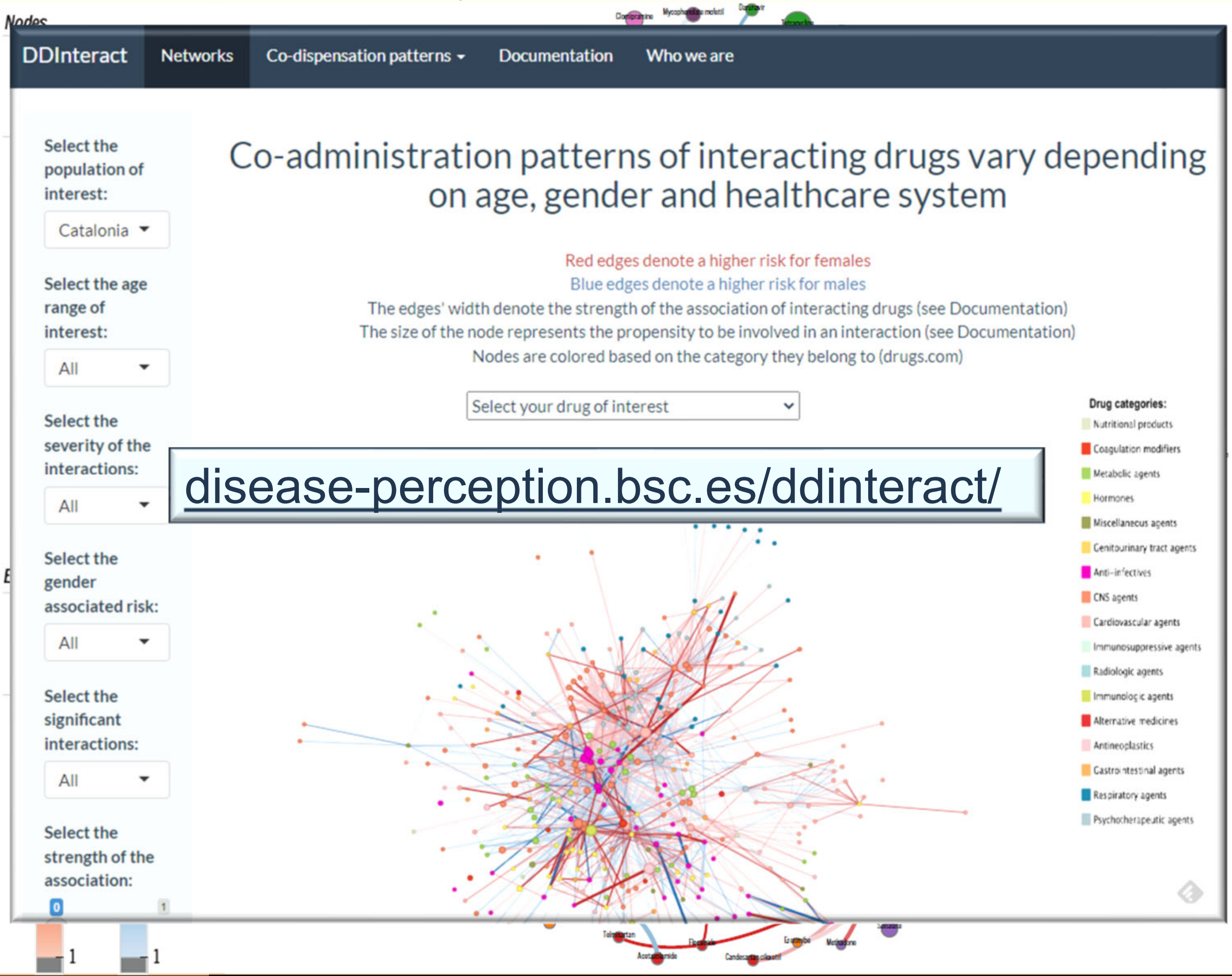
Strength of interaction $\geq$ ***0.18:*** likelihood of joint administration, given administration of i or j).

Sanchez-Valle et al [2023]. *medRxiv* 2023.02.06.23285566,

rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

How is the DDI phenomenon in human populations?

Browsable networks to synthesize information and aid actionable interventions



disease-perception.bsc.es/ddinteract/

Catalonia
814 unique *DrugBank* IDs administered to **5,555,924** patients during **11 years** (Jan 2008-Dec 2018).

Indianapolis
1,228 unique *DrugBank* IDs dispensed to **264,607** patients during **2 years** (Jan 2017–Dec 2018).

Blumenau
140 unique *DrugBank* IDs dispensed to **133,047** patients during **18 months** (Jan 2014–Jun 2015).

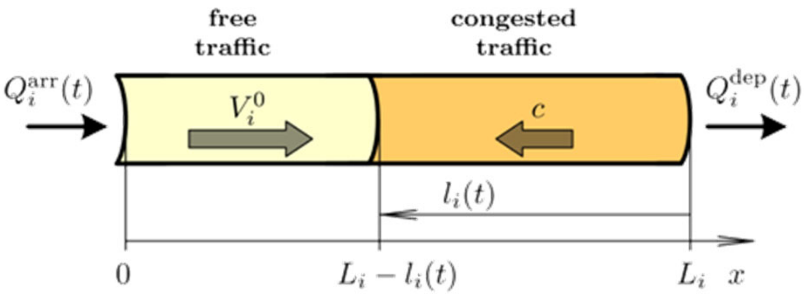
Strength of interaction ≥ 0.18: likelihood of joint administration, given administration of i or j).

Sanchez-Valle et al [2023]. *medRxiv* 2023.02.06.23285566,

BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

Dirk Helbing's Modeling traffic and human group behavior

- Vehicles and people modeled as particles in a fluid medium
  - Free traffic: behaves as a gas
    - Particles move freely
  - Congested traffic: behaves as a liquid
    - movement of particles strongly depends on surrounding dynamics
  - Shock waves
    - emerge from density variations
    - Example in congested traffic
      - The velocity change of a vehicle propagates (with a homogenous time delay) in the opposite direction of traffic as downstream vehicle respond to changes in upstream vehicles
      - propagation speed aprox. -15 km/h (In free traffic = free vehicle velocity).

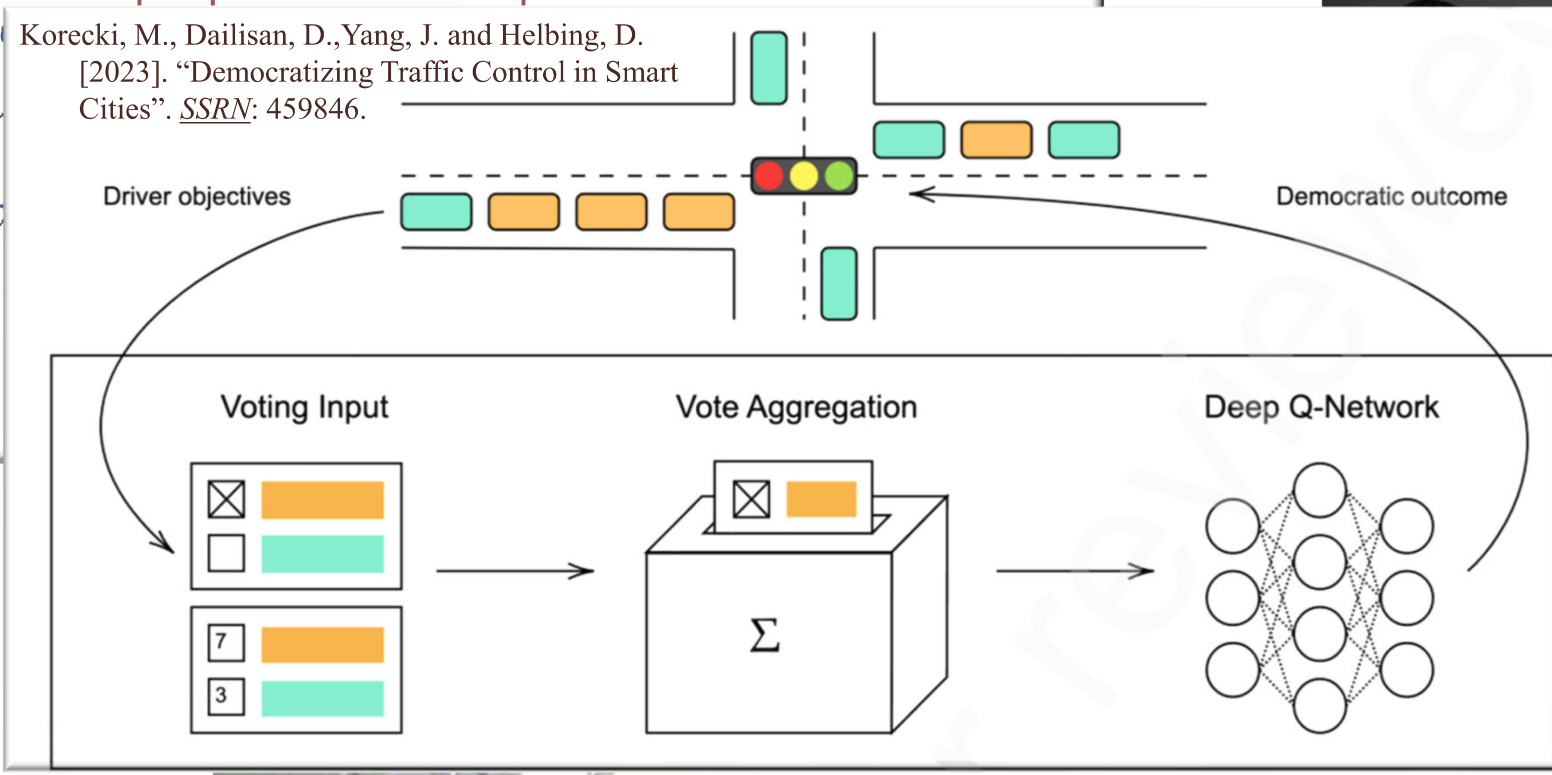


D. Helbing: Traffic and related self-driven many-particle systems. *Reviews of Modern Physics* **73**, 1067-1141 (2003).

Dirk Helbing's Modeling traffic and human group behavior

- Vehicles and people modeled as particles in a fluid medium
  - Fre
  - Cor
  - Sho

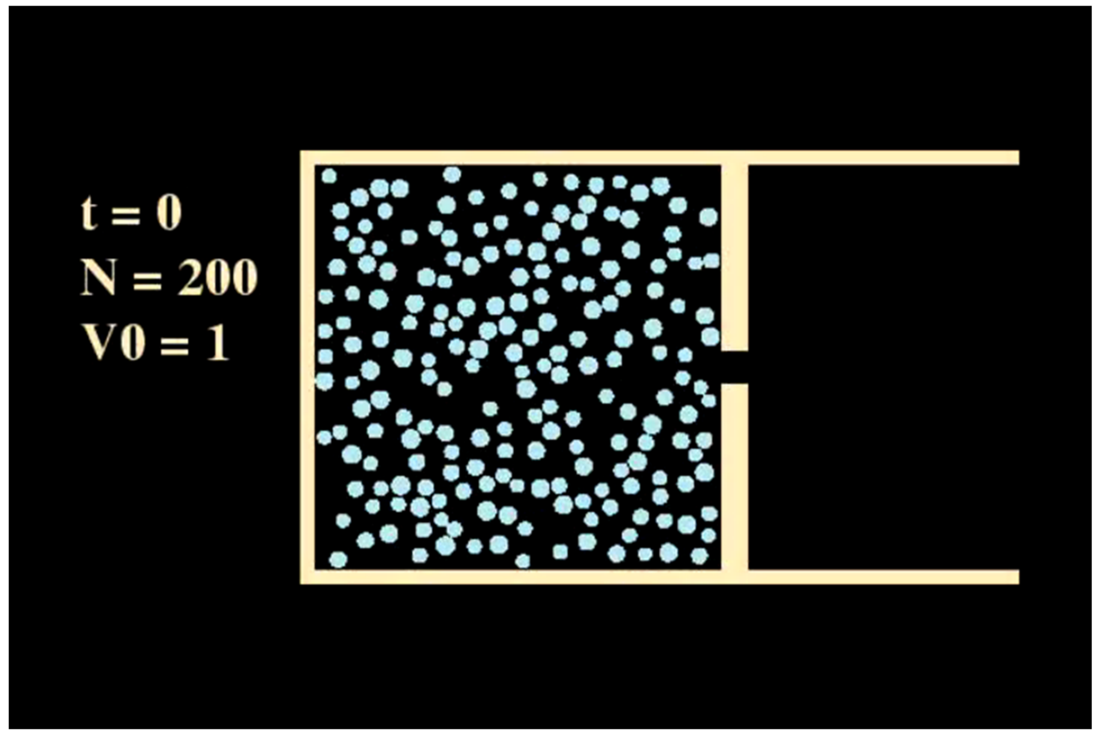
Korecki, M., Dailisan, D.,Yang, J. and Helbing, D. [2023]. "Democratizing Traffic Control in Smart Cities". *SSRN*: 459846.



D. Helbing: Traffic and related self-driven many-particle systems. *Reviews of Modern Physics* **73**, 1067-1141 (2003).

modeling crowd disasters

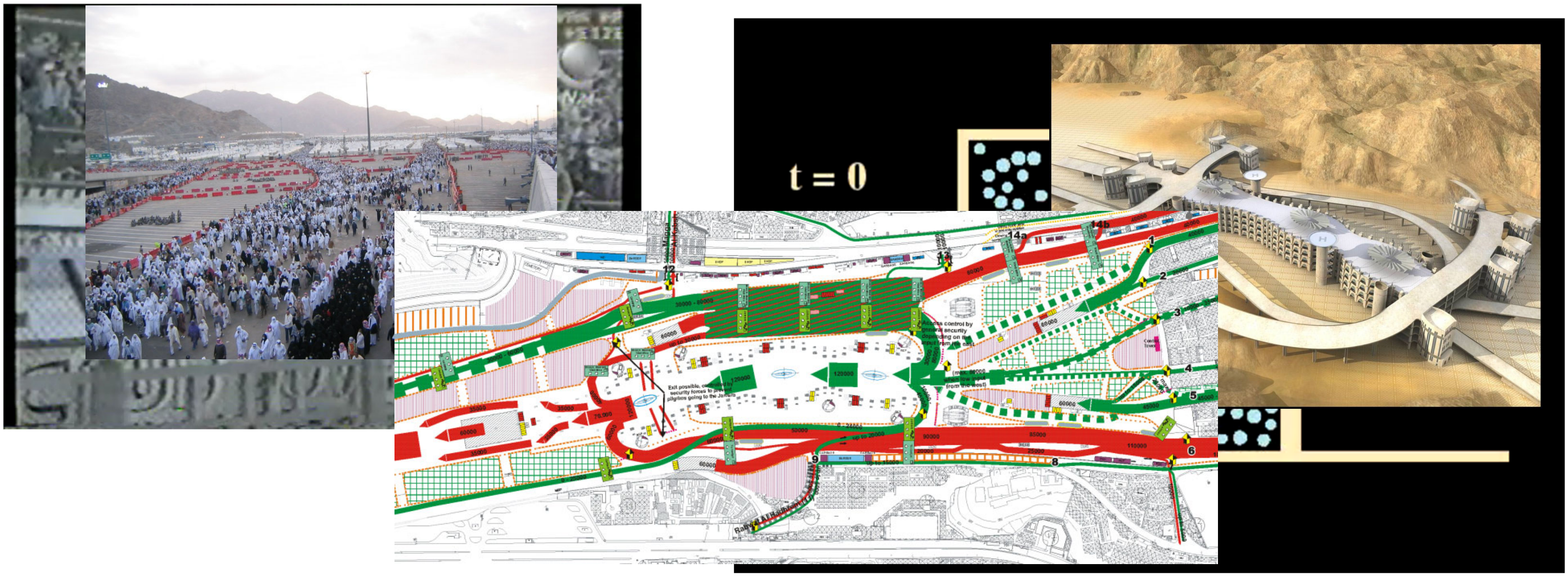
- People modeled as self-driven many-particle systems
- Testing individualistic vs herding behavior as well as environmental solutions



D. Helbing, A. Johansson and H. Z. Al-Abideen (2007) The Dynamics of Crowd Disasters: An Empirical Study. *Physical Review E* 75, 046109.

modeling crowd disasters

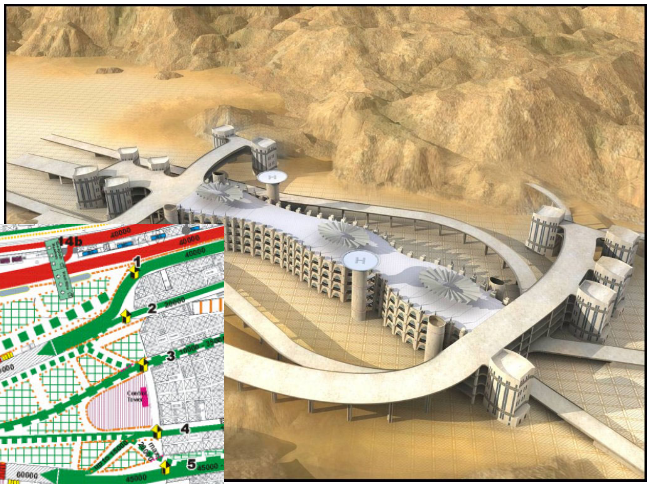
- People modeled as self-driven many-particle systems
- Testing individualistic vs herding behavior as well as environmental solutions



D. Helbing, A. Johansson and H. Z. Al-Abideen (2007) The Dynamics of Crowd Disasters: An Empirical Study. *Physical Review E* 75, 046109.

modeling crowd disasters

- People modeled as self-driven many-particle systems
- Testing individualistic vs herding behavior as well as environmental solutions

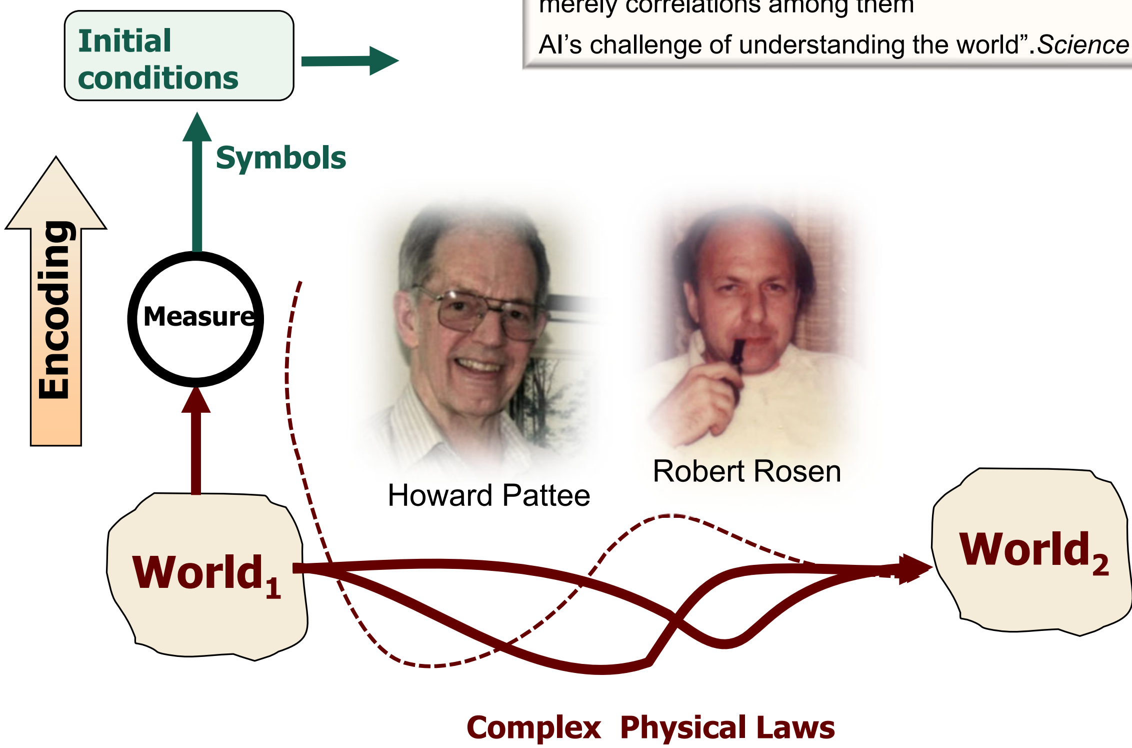


D. Helbing, A. Johansson and H. Z. Al-Abideen (2007) The Dynamics of Crowd Disasters: An Empirical Study. *Physical Review E* 75, 046109.

may work in complex interrelated domain (with rare control events)

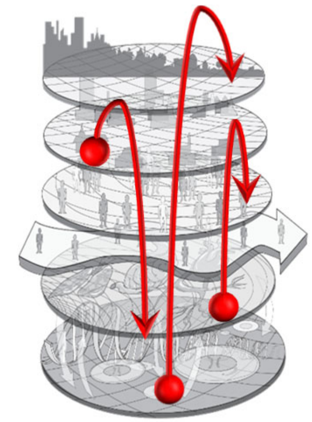
Melanie Mitchell: Current AI systems seem to be lacking a crucial aspect of human intelligence: rich internal models of the world. A tenet of modern cognitive science is that humans are not simply conditioned-reflex machines; instead, we have inside our heads abstracted models of the physical and social worlds that reflect the causes of events rather than merely correlations among them

AI's challenge of understanding the world". *Science* **382**,eadm8175(2023)



Howard Pattee

Robert Rosen

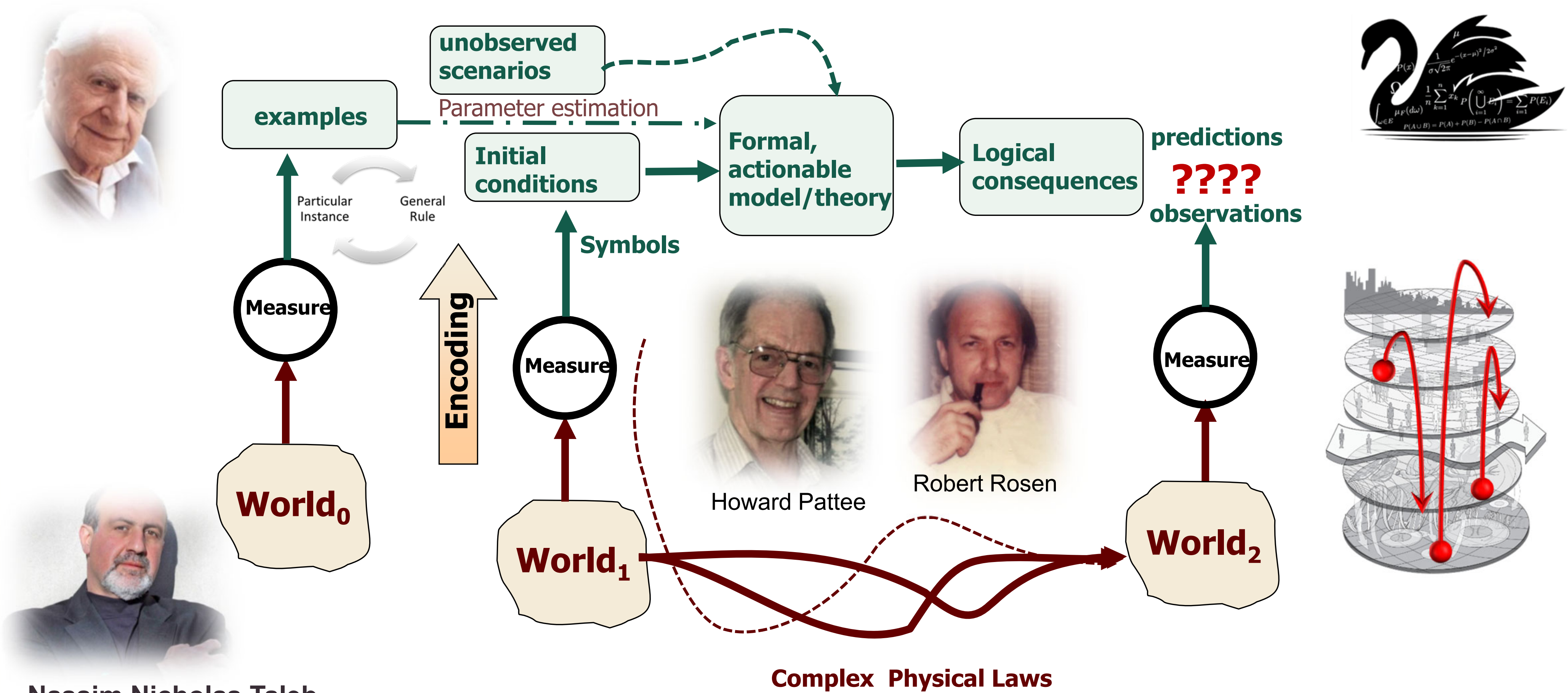


Nassim Nicholas Taleb

"predictions of events **depend** more and more **on theories** when their probability is small and system is **complex**"

BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

may work in complex interrelated domain (with rare control events)



Nassim Nicholas Taleb

"predictions of events **depend** more and more **on theories** when their probability is small and system is **complex**"

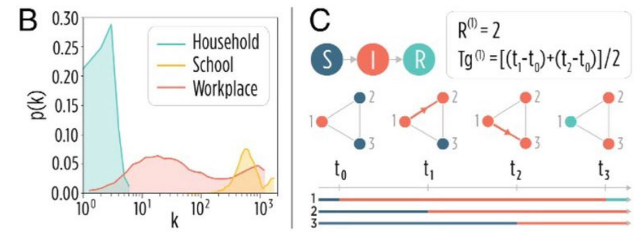
mechanistic models, estimated parameters

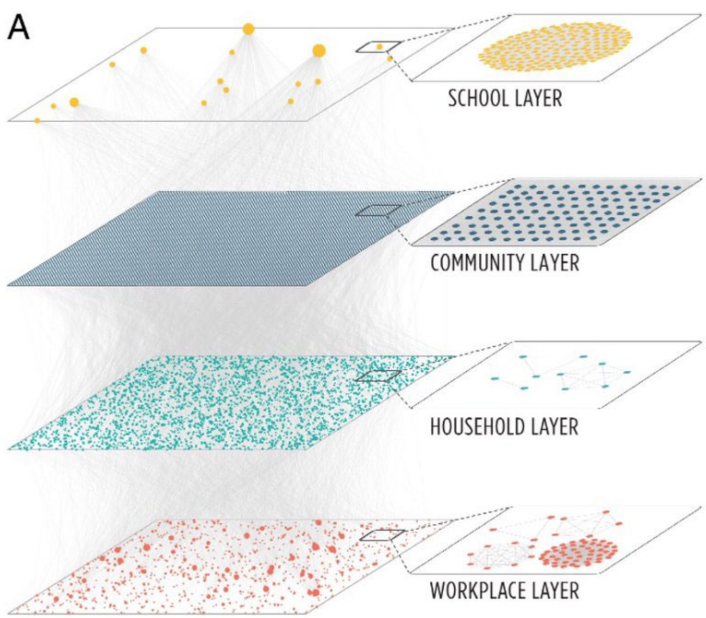
Measurability of the epidemic reproduction number in data-driven contact networks

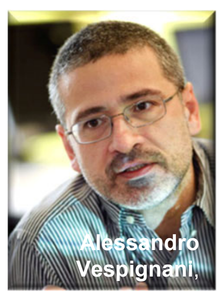
Quan-Hui Liu[a,b,c], Marco Ajelli[c,d], Alberto Aleta[e,f], Stefano Merler[d], Yamir Moreno[e,f,g], and Alessandro Vespignani[c,g,1]

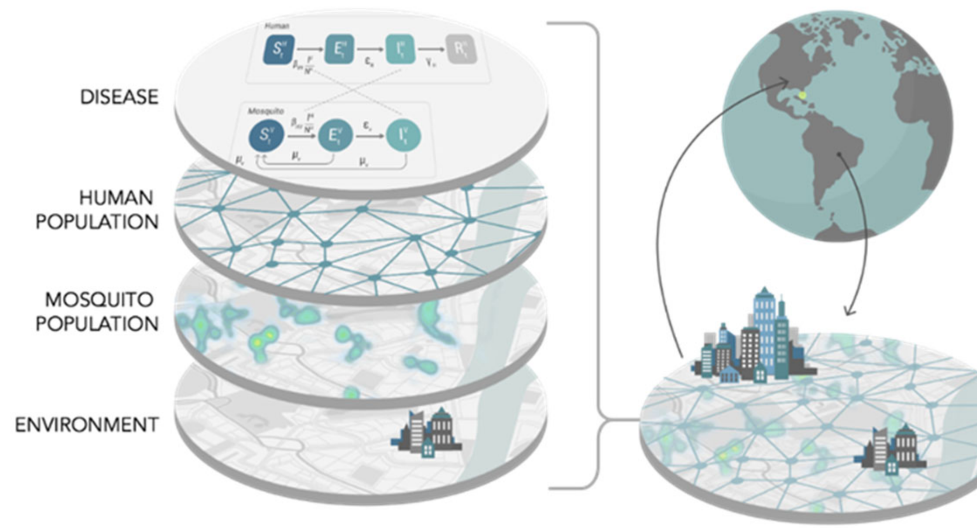
[a]Web Sciences Center, University of Electronic Science and Technology of China, Chengdu 611731, Sichuan, People's Republic of China; [b]Big Data Research Center, University of Electronic Science and Technology of China, Chengdu 611731, Sichuan, People's Republic of China; [c]Laboratory for the Modeling of Biological and Socio-Technical Systems, Northeastern University, Boston, MA 02115; [d]Bruno Kessler Foundation, 38123 Trento, Italy; [e]Institute for Biocomputation and Physics of Complex Systems, University of Zaragoza, 50018 Zaragoza, Spain; [f]Department of Theoretical Physics, University of Zaragoza, 50009 Zaragoza, Spain; and [g]ISI Foundation, 10126 Turin, Italy

Edited by Simon A. Levin, Princeton University, Princeton, NJ, and approved October 16, 2018 (received for review June 27, 2018)

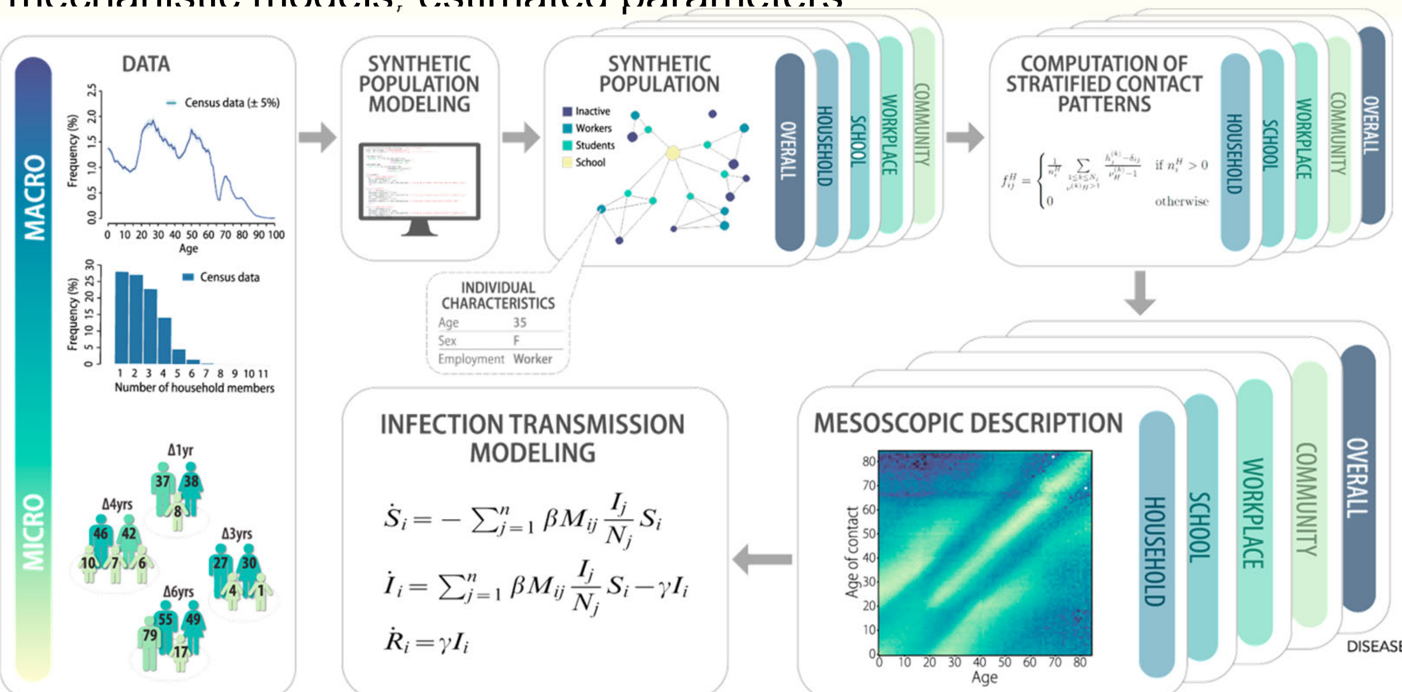


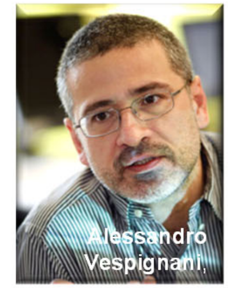






mechanistic models, estimated parameters

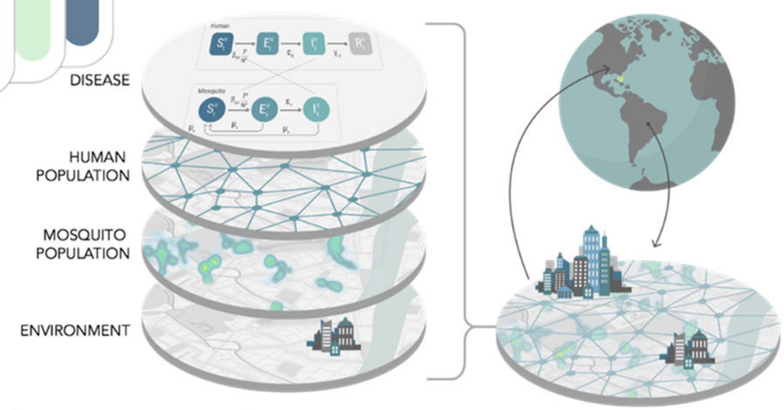




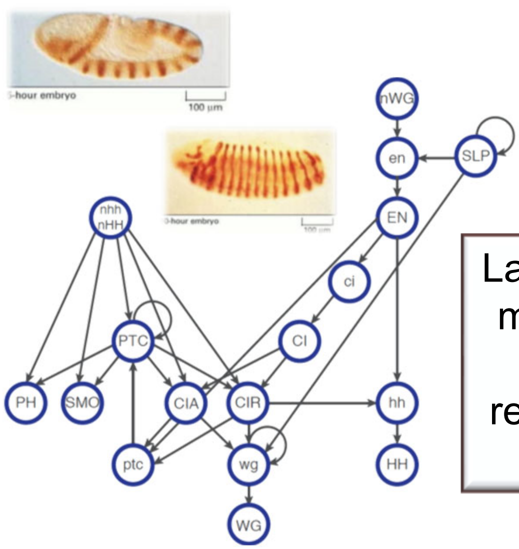
nature COMMUNICATIONS

Inferring high-resolution human mixing patterns for disease modeling

Dina Mistry [1,2], Maria Litvinova [2,3,4], Ana Pastore y Piontti[2], Matteo Chinazzi[2], Laura Fumanelli[5], Marcelo F. C. Gomes [6], Syed A. Haque [2], Quan-Hui Liu[7], Kunpeng Mu[2], Xinyue Xiong[2], M. Elizabeth Halloran [8,9], Ira M. Longini Jr.[10], Stefano Merler[5], Marco Ajelli [2,4✉] & Alessandro Vespignani [2,3✉]



biochemical dynamics from synthesis of experimental data

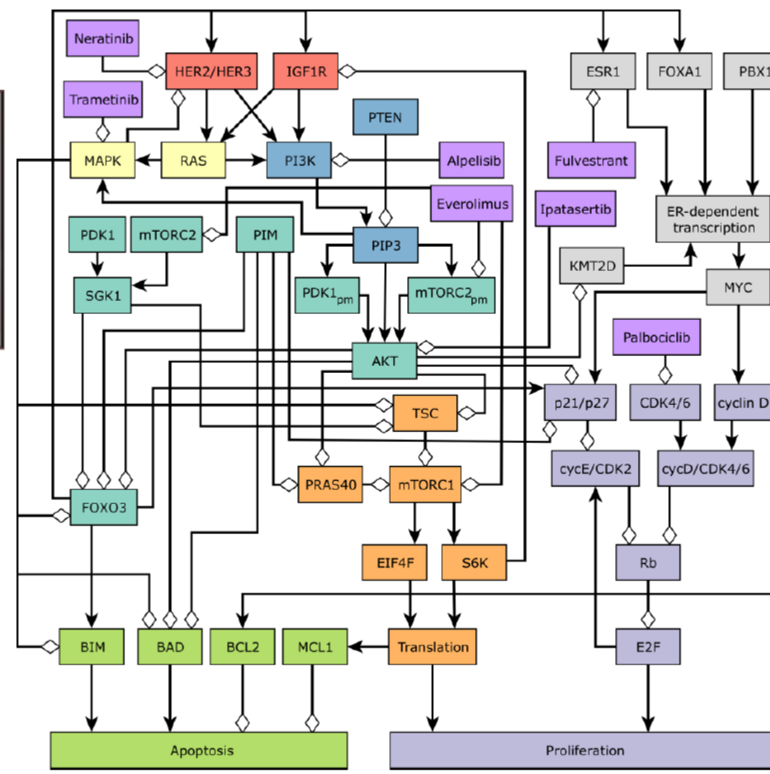


Node	*State − TransitionFunction*
SLP_i^{t+1}	$\leftarrow 0$ if $i=1 \vee i=2$; 1 if $i=3 \vee i=4$;
wg_i^{t+1}	$\leftarrow (CIA_i^t \wedge SLP_i^t \wedge \neg CIR_i^t) \vee (wg_i^t \wedge (CIA_i^t \vee SLP_i^t) \wedge \neg CIR_i^t)$
WG_i^{t+1}	$\leftarrow wg_i^t$
en_i^{t+1}	$\leftarrow (WG_{i-1}^t \vee WG_{i+1}^t) \wedge \neg SLP_i^t$
EN_i^{t+1}	$\leftarrow en_i^t$
hh_i^{t+1}	$\leftarrow EN_i^t \wedge \neg CIR_i^t$
HH_i^{t+1}	$\leftarrow hh_i^t$
ptc_i^{t+1}	$\leftarrow CIA_i^t \wedge \neg EN_i^t \wedge \neg CIR_i^t$
PTC_i^{t+1}	$\leftarrow ptc_i^t \vee (PTC_i^t \wedge \neg HH_{i-1}^t \wedge \neg HH_{i-1}^t)$

A network modeling approach to elucidate drug resistance mechanisms and predict combinatorial drug treatments in breast cancer

Jorge G. T. Zañudo[1,2,3,*] and Réka Albert[1,4,&]

Large-scale literature synthesis for discrete modeling of within-cell **oncogenic signal transduction**, recapitulates known resistance PI3K inhibitors. Suggests novel combinatorial interventions.



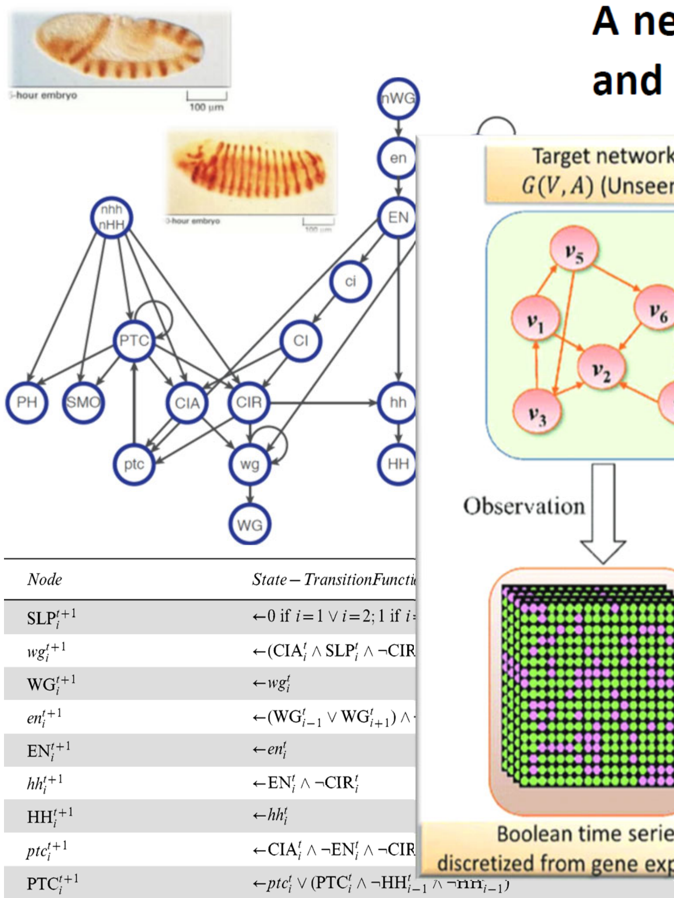
Helikar et al. [2012] *BMC Syst. Biol.* **6**, 96.
Zañudo, Scaltriti, & Albert. *Cancer convergence* **1**.1 (2017): 1-25.
Albert & Othmer [2003]. *J. Theor. Bio.* **223**: 1-18.

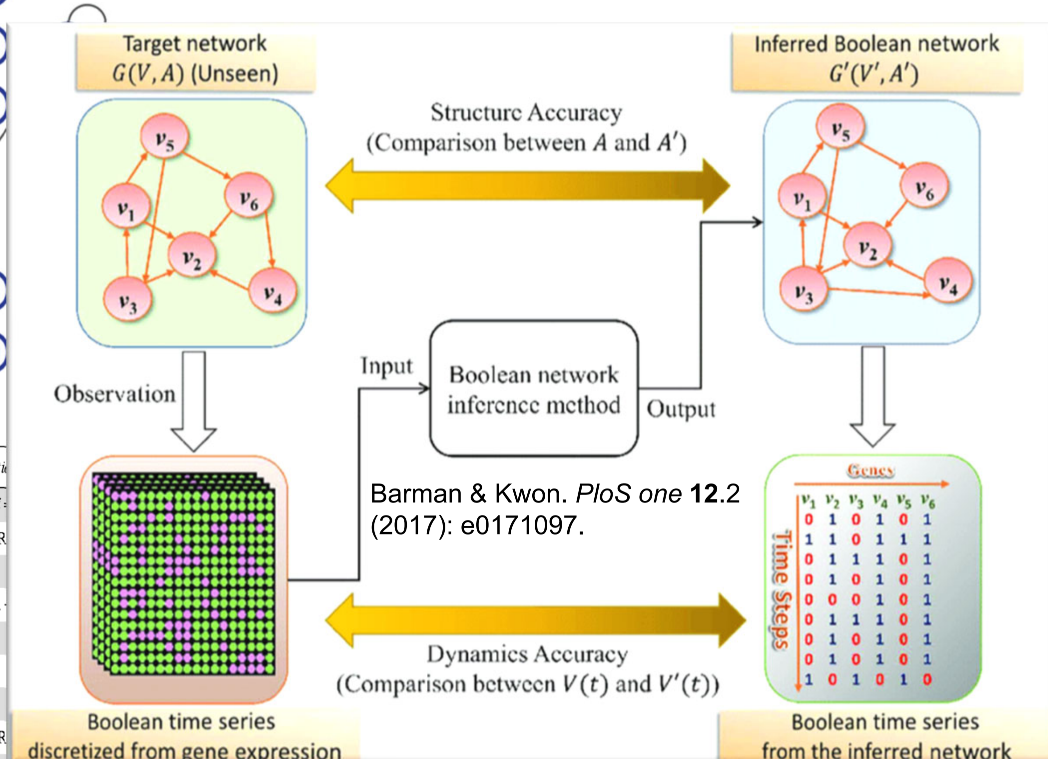
Cell Collective

BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

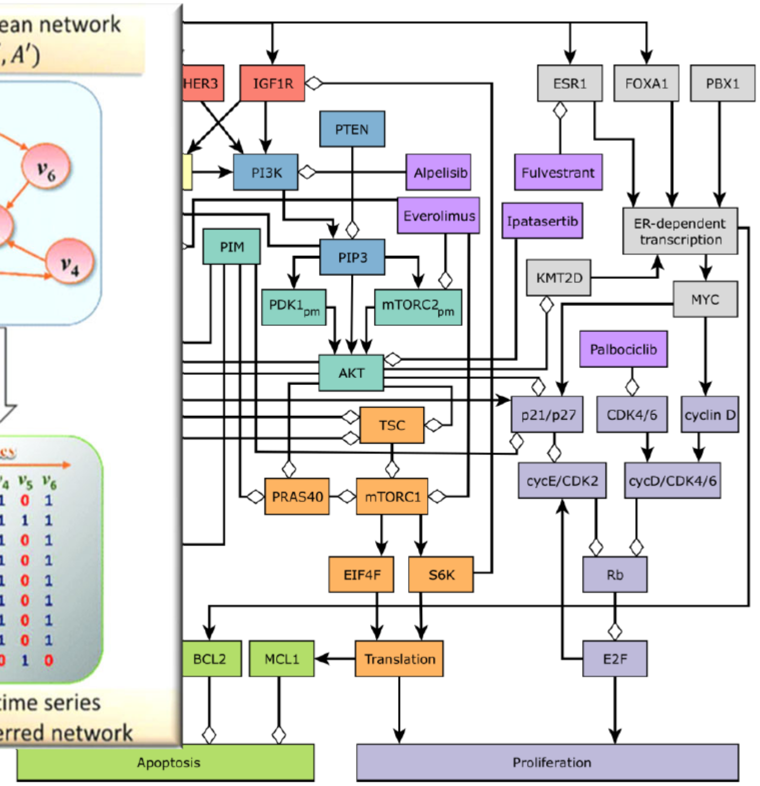
biochemical dynamics from synthesis of experimental data

A network modeling approach to elucidate drug resistance mechanisms and predict combinatorial drug treatments in breast cancer





Barman & Kwon. *PloS one* **12**.2 (2017): e0171097.



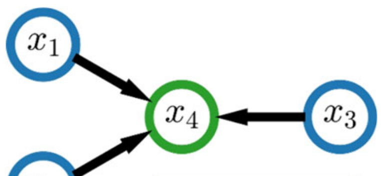
Helikar et al. [2012] *BMC Syst. Biol.* **6**, 96.
Zañudo, Scaltriti, & Albert. *Cancer convergence* **1**.1 (2017): 1-25.
Albert & Othmer [2003]. *J. Theor. Bio.* **223**: 1-18.

Cell Collective

BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

quantifying redundancy in automata networks

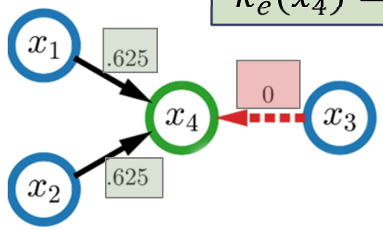
with the effective graph (nonlinear collective measure of effective control)

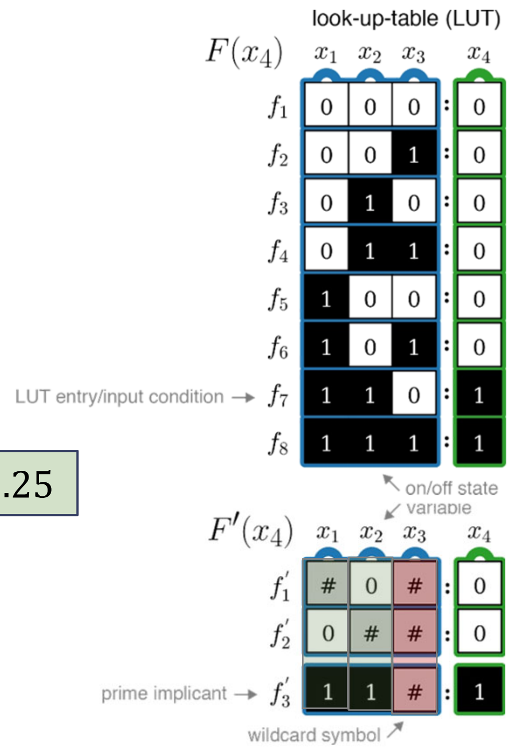


$k(x_4) = 3$

$x_4 = x_1 \wedge x_2$

$k_e(x_4) = 1.25$





Prime Implicants (Quine-McCluskey)

minimal transition control: set of wildcard schemata is **DNF** of prime implicants (Blake Canonical Form)

Measuring *redundancy* and its dual *effectiveness*

input redundancy:

$k_r(x)$ = mean number of "#" in LUT

$$k_r(x_4) = \frac{1 \times 2 + 2 \times 6}{8} = 1.75$$

effective connectivity:

$$k_e(x) = k(x) - k_r(x)$$

$$k_e(x_i) = \sum_{j=1}^{k} e_{ji}$$

edge effectiveness

$$r_{ji} = \frac{\sum_{f_\alpha \in F_i} \operatorname*{avg}_{\upsilon : f_\alpha \in \Upsilon_\upsilon^i} (j \rightarrowtail \#)_\upsilon}{|F_i|},$$

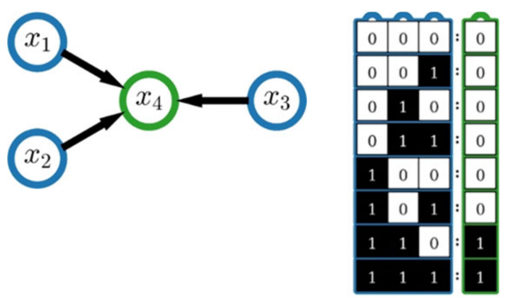
$$e_{ji} = 1 - r_{ji}.$$

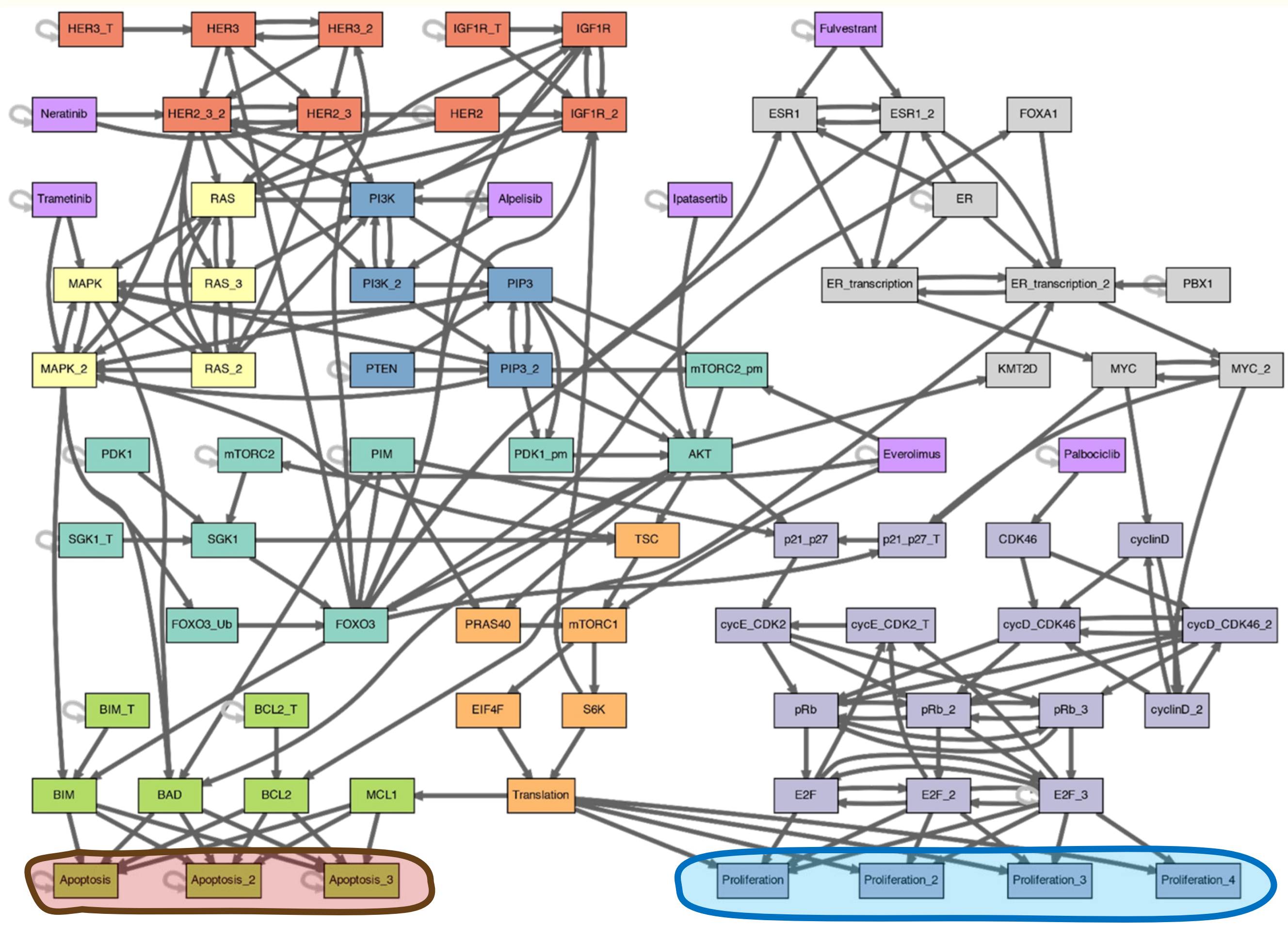
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.

BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

effective graph: redundancy and control in biochemical regulation

(actionable) model of pharmacology in ER+ breast cancer

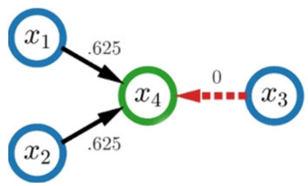




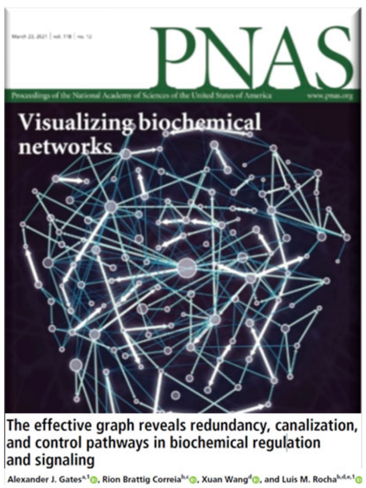
Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.
Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.
Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physyology* **9:** 1046.
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Parmer, Rocha & Radicchi [2022]. *Nature Communications*. **13**, 3457.

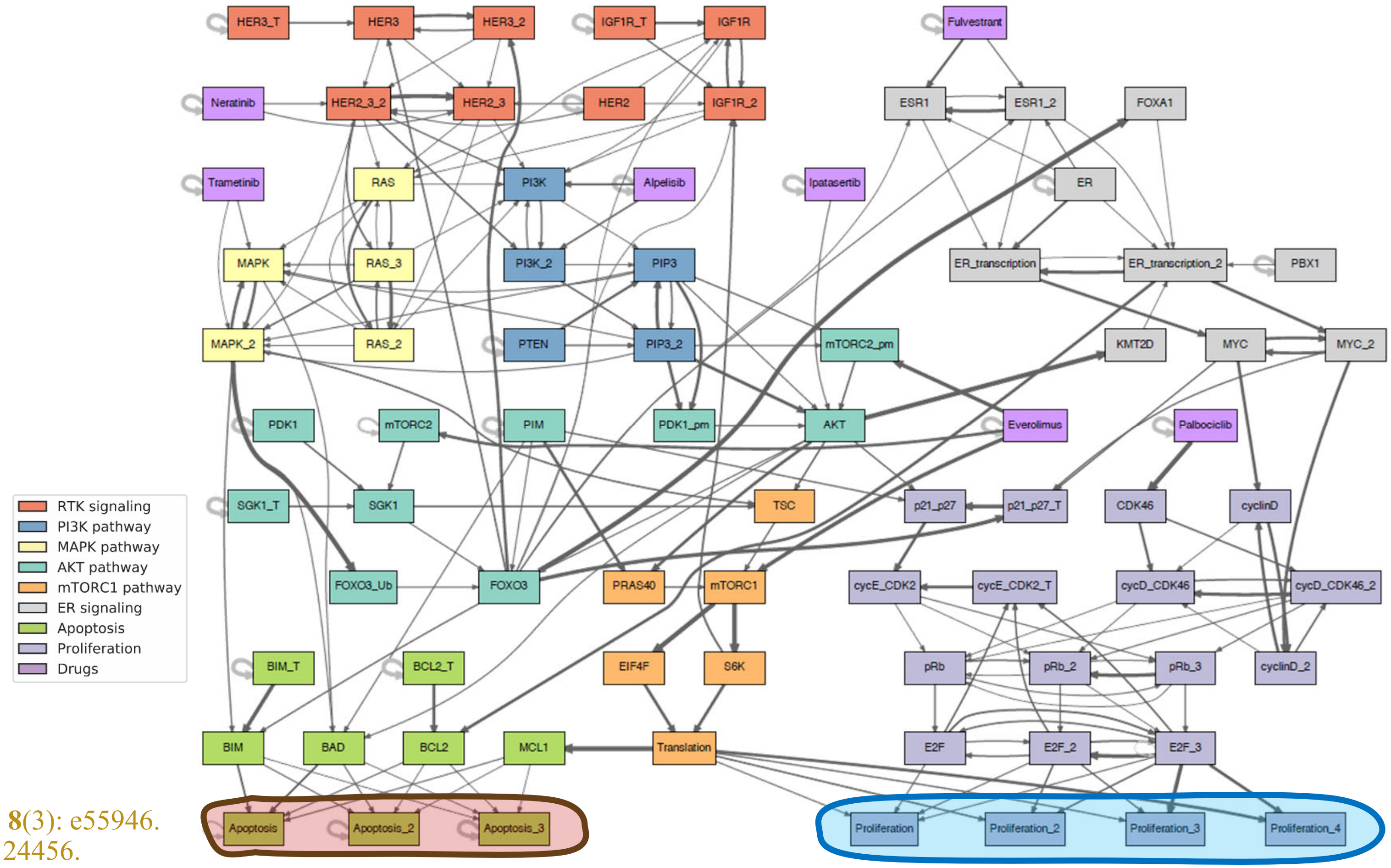
BINGHAMTON UNIVERSITY STATE UNIVERSITY OF NEW YORK
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

(actionable) model of pharmacology in ER+ breast cancer



#	0	#	:	0
0	#	#	:	0
1	1	#	:	1



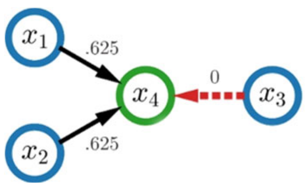


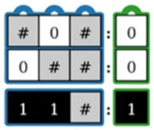
Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.
Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.
Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physyology* **9:** 1046.
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Parmer, Rocha & Radicchi [2022]. *Nature Communications*. **13**, 3457.

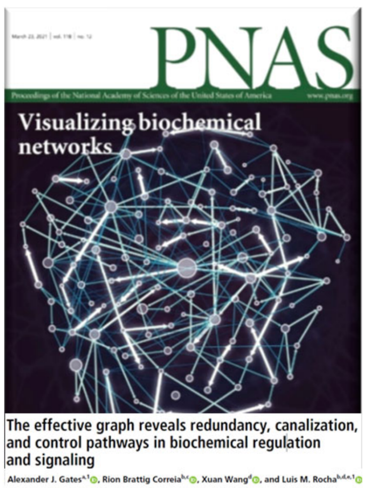
pypi.python.org/pypi/cana

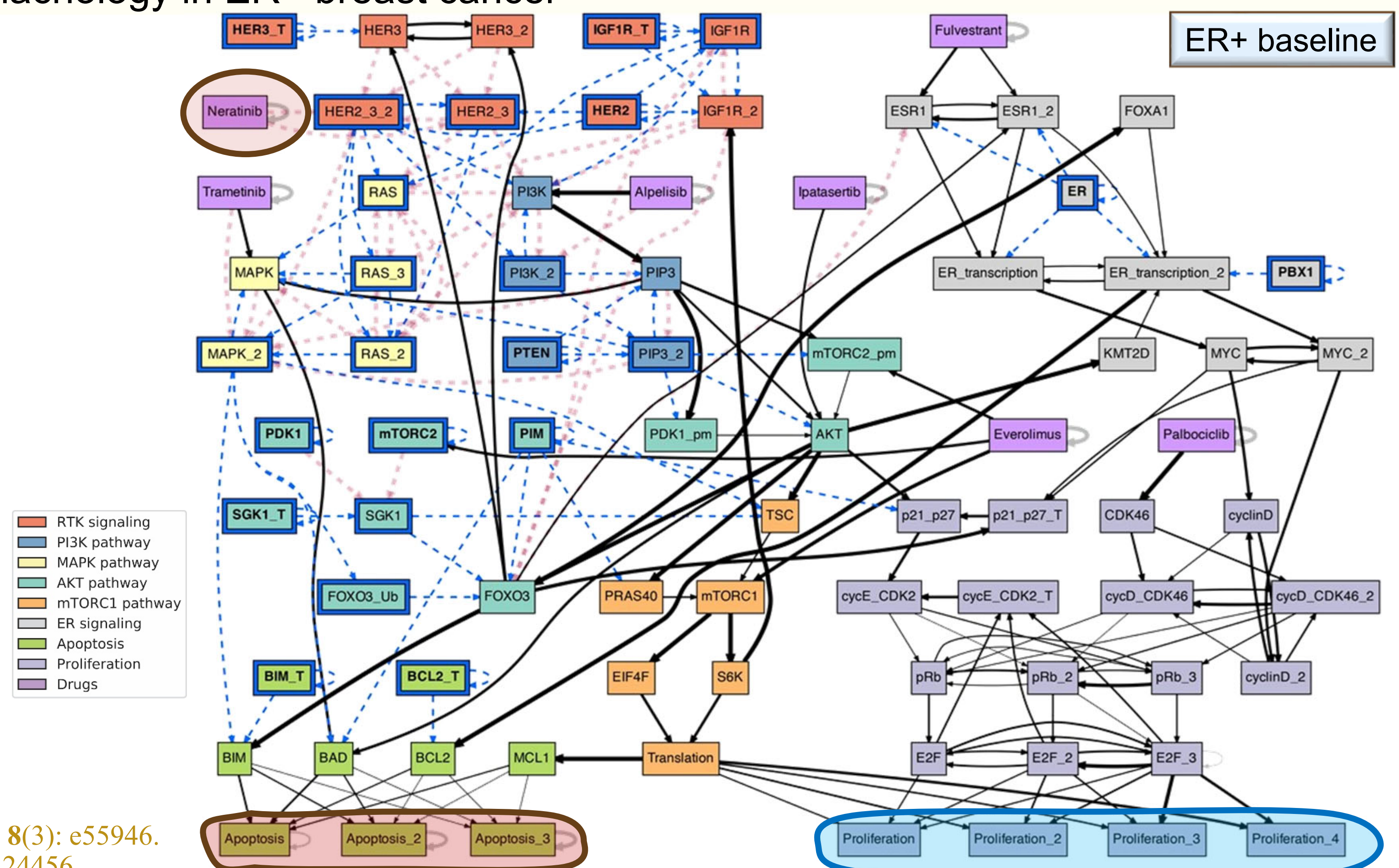
rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

(actionable) model of pharmacology in ER+ breast cancer







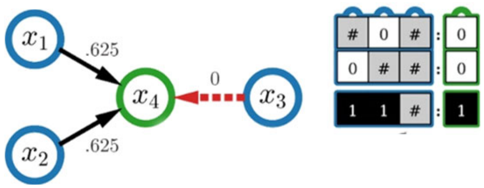


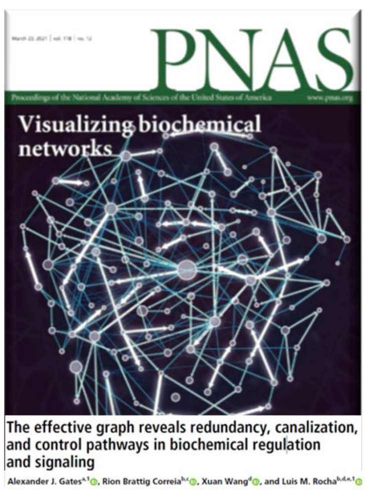
Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.
Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.
Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physyology* **9:** 1046.
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Parmer, Rocha & Radicchi [2022]. *Nature Communications*. **13**, 3457.

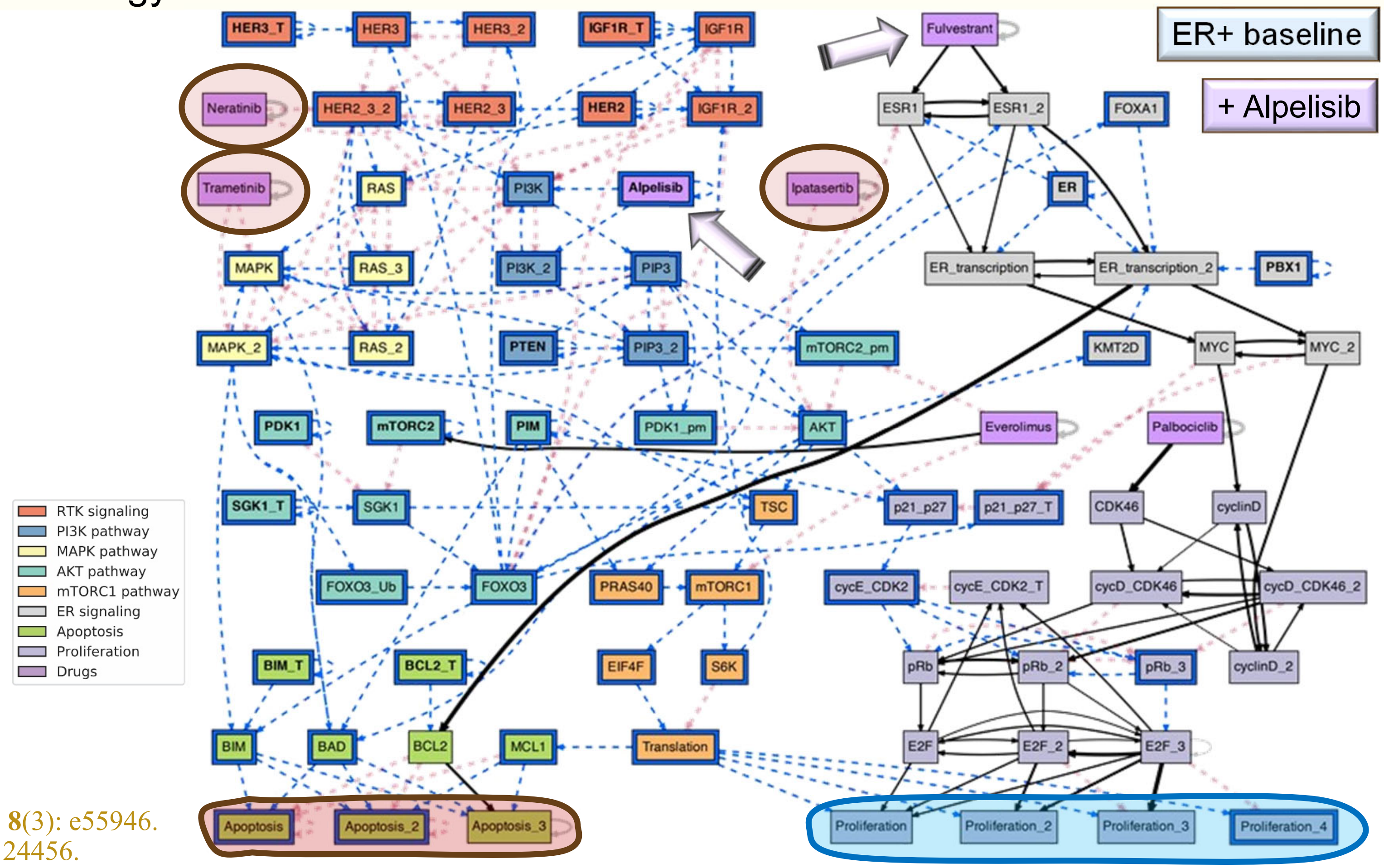
pypi.python.org/pypi/cana

rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

(actionable) model of pharmacology in ER+ breast cancer





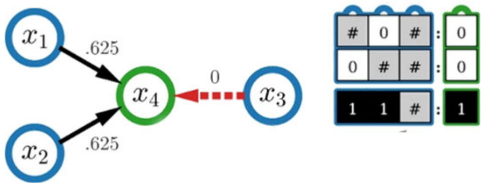


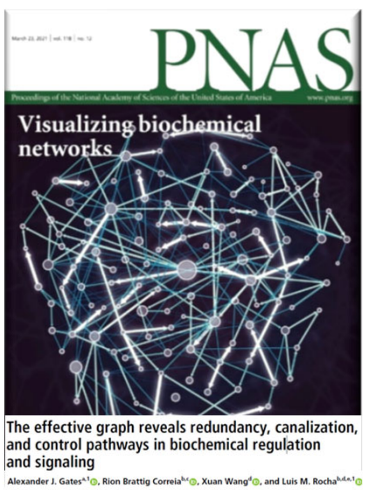
Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.
Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.
Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physyology* **9:** 1046.
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Parmer, Rocha & Radicchi [2022]. *Nature Communications*. **13**, 3457.

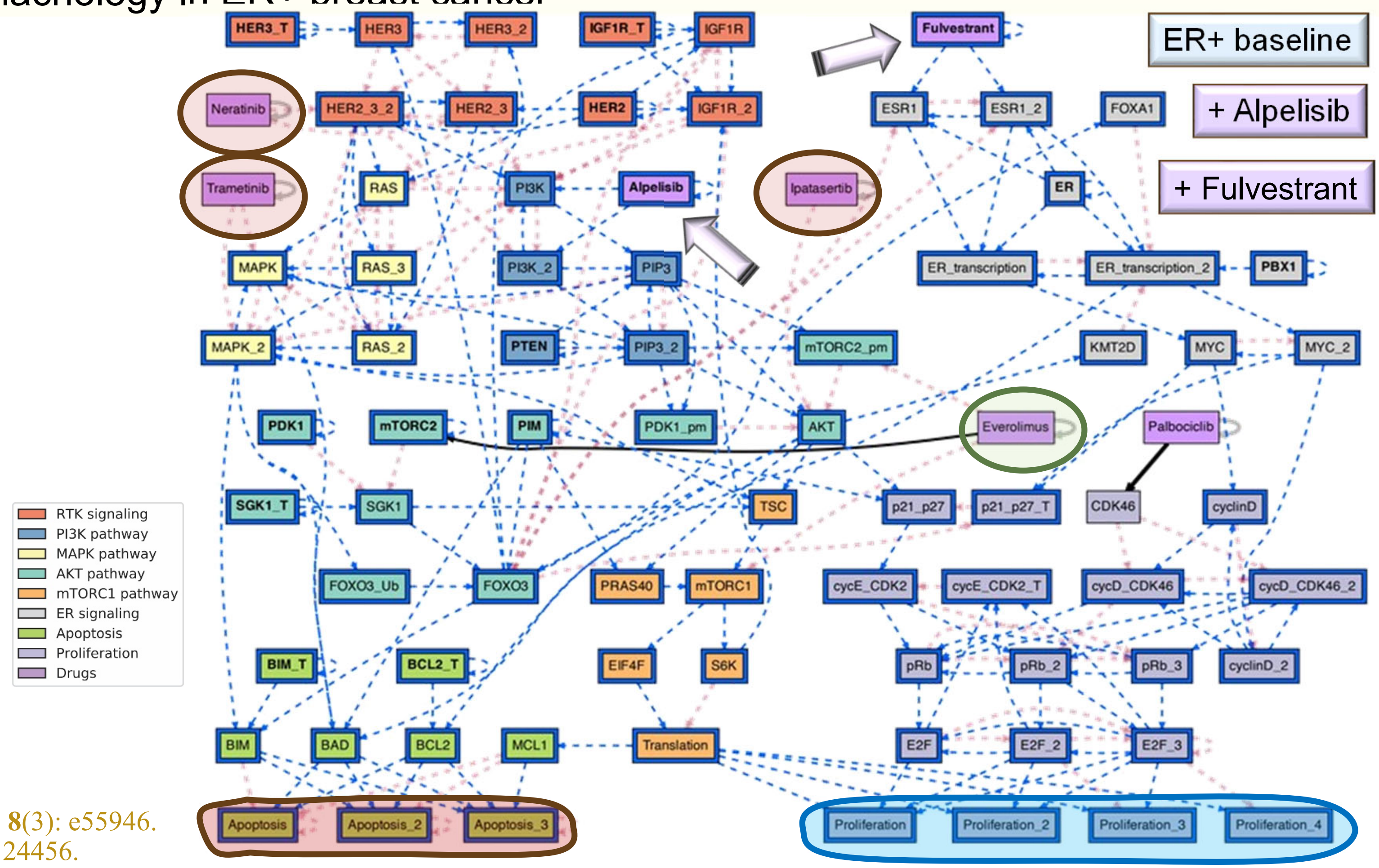
pypi.python.org/pypi/cana

rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

(actionable) model of pharmacology in ER+ breast cancer





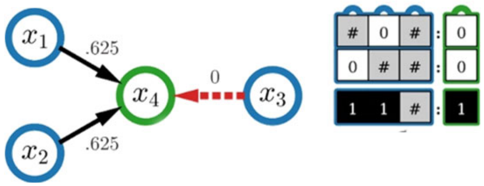


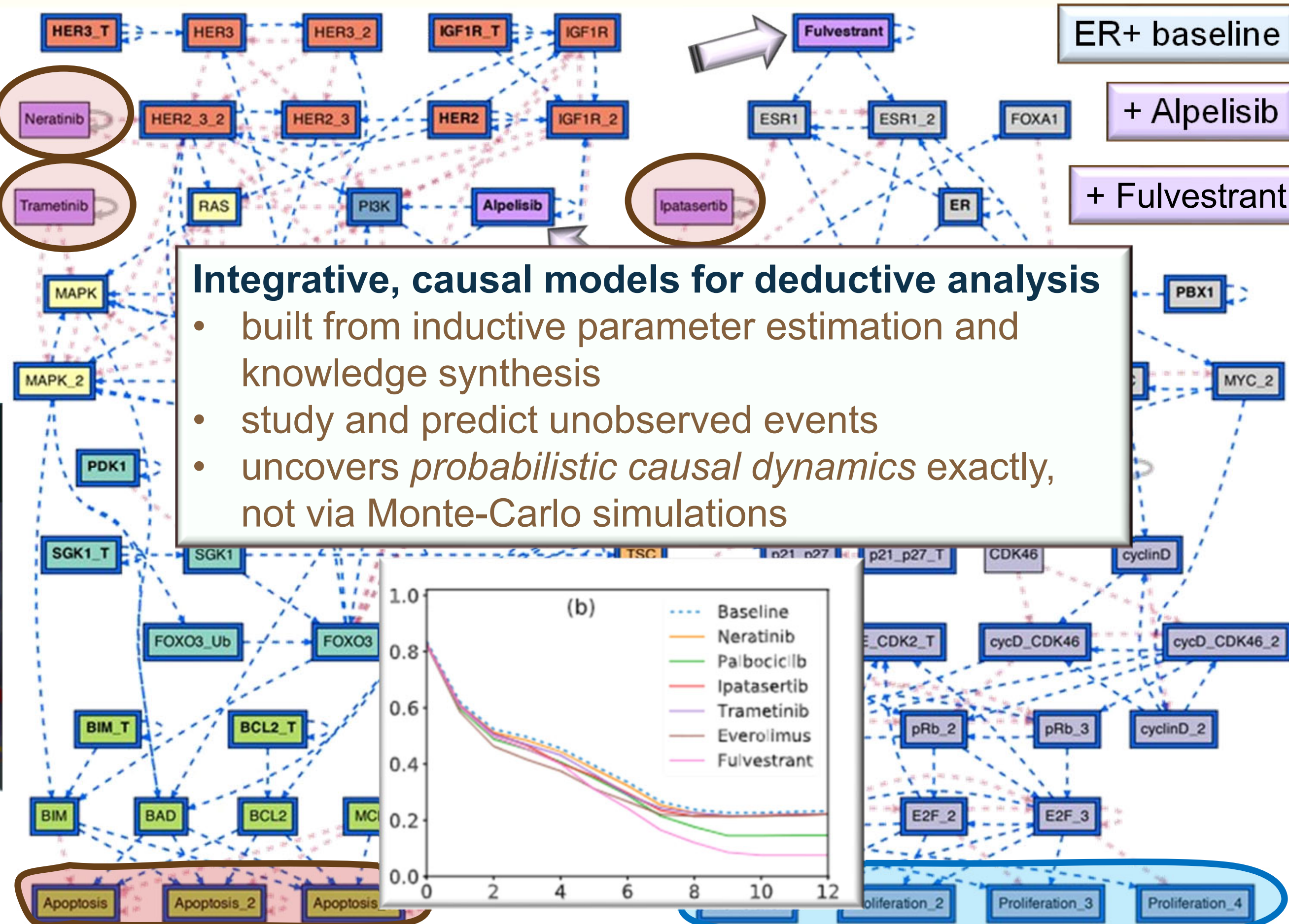
Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.
Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.
Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physyology* **9**: 1046.
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Parmer, Rocha & Radicchi [2022]. *Nature Communications*. **13**, 3457.

pypi.python.org/pypi/cana

rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

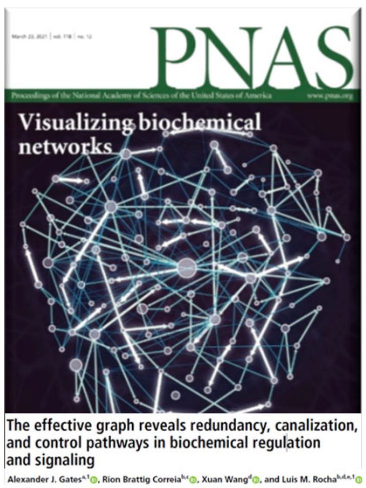
(actionable) model of pharmacology in ER+ breast cancer

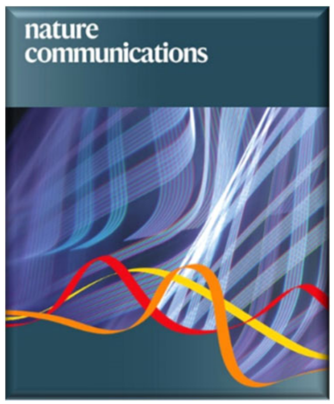




Integrative, causal models for deductive analysis

- built from inductive parameter estimation and knowledge synthesis
- study and predict unobserved events
- uncovers *probabilistic causal dynamics* exactly, not via Monte-Carlo simulations





Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.
Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.
Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physyology* **9:** 1046.
Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.
Parmer, Rocha & Radicchi [2022]. *Nature Communications*. **13**, 3457.

pypi.python.org/pypi/cana

rocha@binghamton.edu
casci.binghamton.edu/academics/ssie501

readings

- Class Book
  - Klir, G.J. [2001]. *Facets of systems science*. Springer.
- Papers and other materials
  - Module 4 – Multi-level Complexity
    - Reading and Discussion Group 5
      - Theise, N.D., and M.C. Kafatos. [2013]. "Complementarity in Biological Systems: A Complexity View." *Complexity* **18** (6): 11-20.
      - Gallotti, Riccardo, Giulia Bertagnolli, and Manlio De Domenico (2021). “Unraveling the Hidden Organisation of Urban Systems and Their Mobility Flows.” *EPJ Data Science* **10** (1).
      - Pescosolido, Bernice A., et al. "Linking genes-to-global cultures in public health using network science." *Handbook of applied system science* (2016): 25-48.
        - Optional: Mabry, Patricia L., and Robert M. Kaplan. “Systems Science: A Good Investment for the Public’s Health.” Health Education & Behavior 40, no. 1_suppl (October 2013):Future Modules