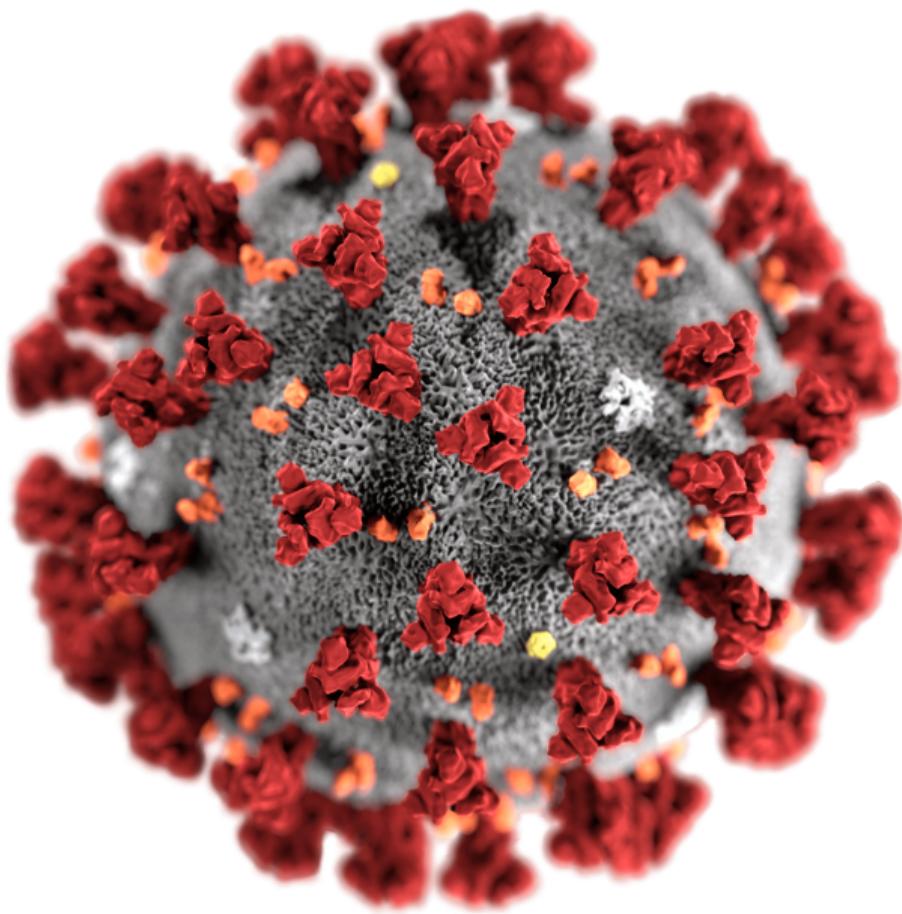


Pre-read for Tuesday, November 3: Disease modeling

Matthew J. Salganik

COS 597E/SOC 555 Limits to prediction
Fall 2020, Princeton University



<https://phil.cdc.gov/Details.aspx?pid=23312>

THE INTERPRETER

R0, the Messy Metric That May Soon Shape Our Lives, Explained

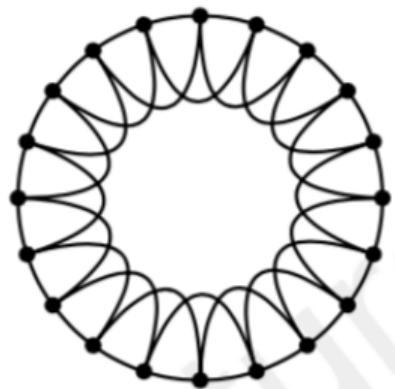
‘R-naught’ represents the number of new infections estimated to stem from a single case. You may be hearing a lot about this.

Collective dynamics of 'small-world' networks

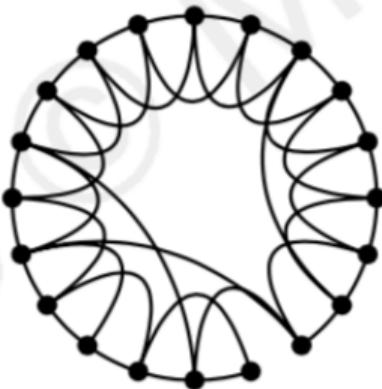
Duncan J. Watts* & Steven H. Strogatz

*Department of Theoretical and Applied Mechanics, Kimball Hall,
Cornell University, Ithaca, New York 14853, USA*

Regular



Small-world



Random

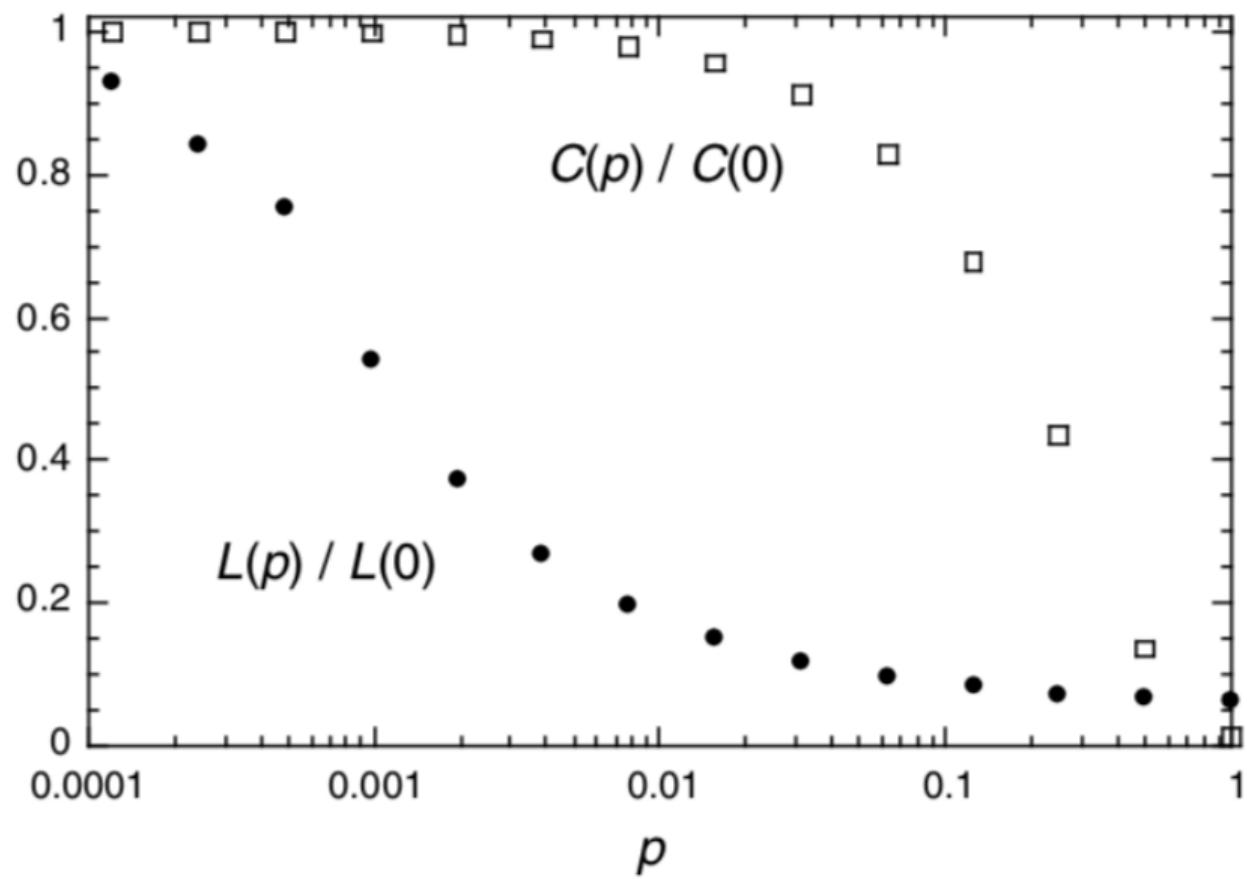


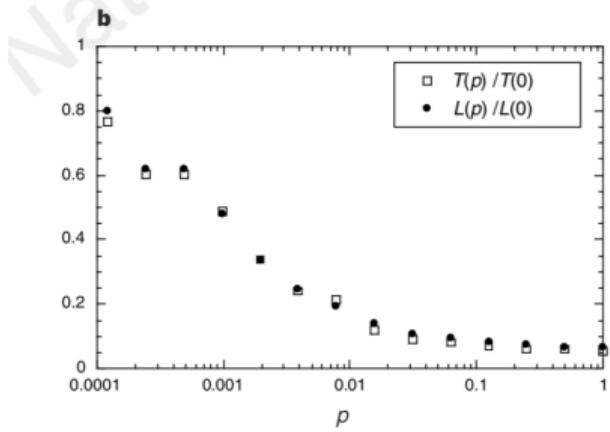
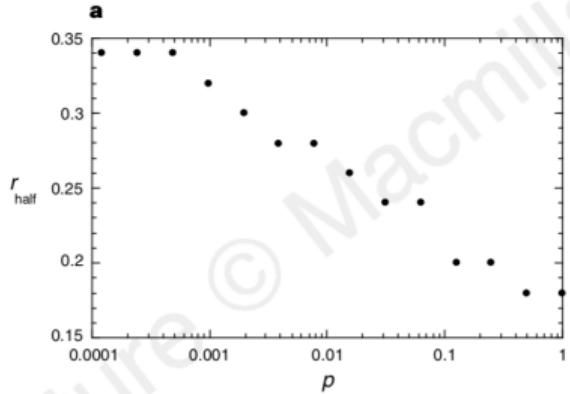
$p = 0$

→

$p = 1$

Increasing randomness





Reading notes:

- ▶ What does it mean for predictability if the disease dynamics depend so sensitively on a single parameter that is hard to measure? What if that sensitivity is only in a particular region of values?

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- ▶ What does it mean for predictability if the disease dynamics depend so sensitively on a single parameter that is hard to measure? What if that sensitivity is only in a particular region of values?
- ▶ This is a transformational paper in the study of networks so enjoy it

Time evolution of predictability of epidemics on networks

Petter Holme^{1, 2, 3, *} and Taro Takaguchi^{4, 5}

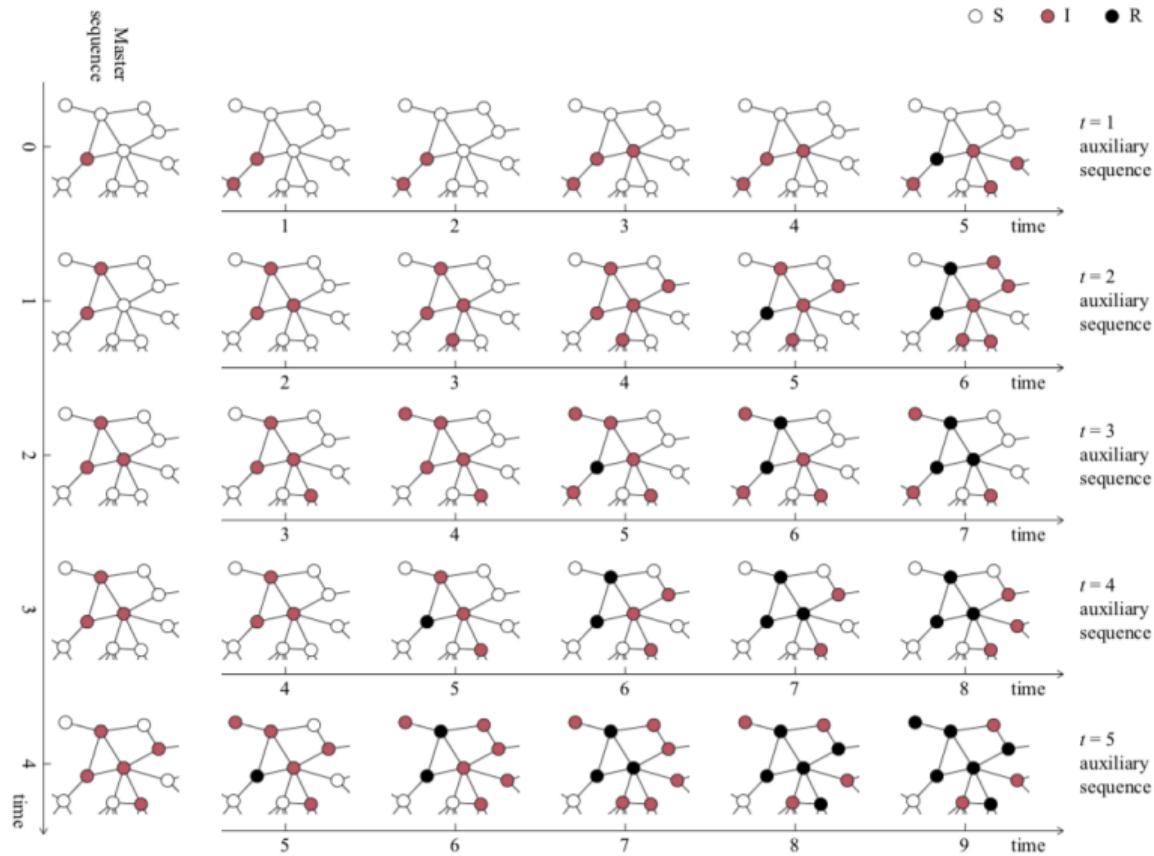
¹*Department of Energy Science, Sungkyunkwan University, Suwon 440-746, Korea*

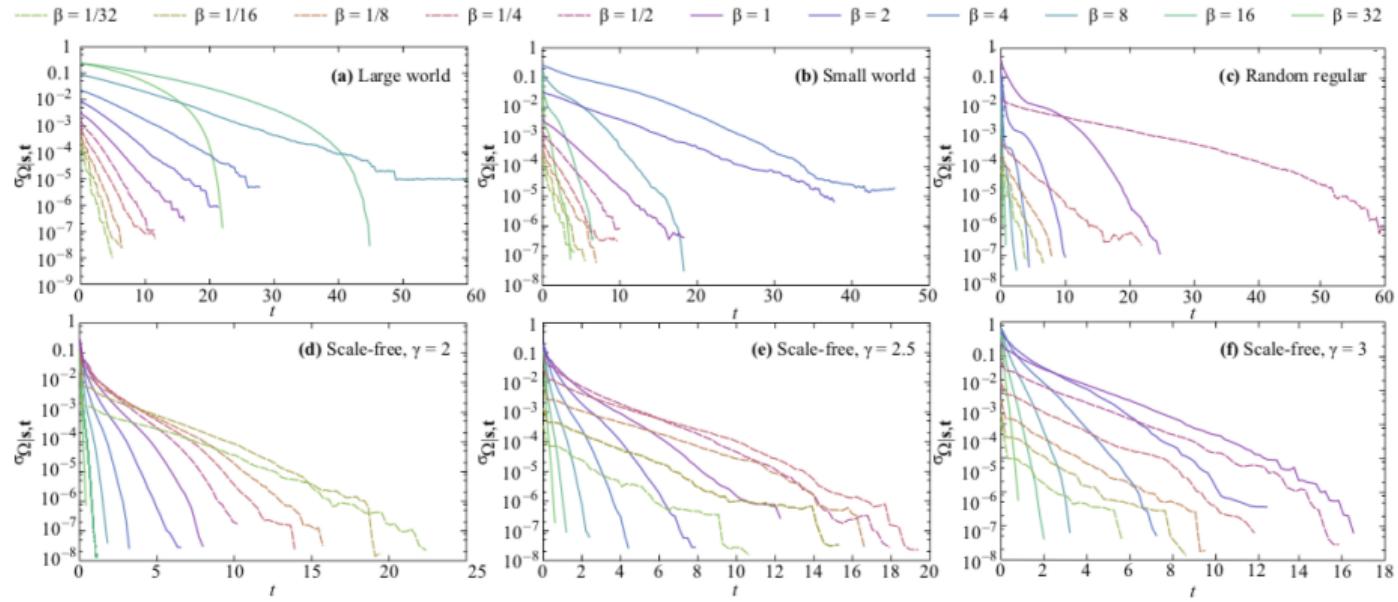
²*Department of Physics, Umeå University, 90187 Umeå, Sweden*

³*Department of Sociology, Stockholm University, 10961 Stockholm, Sweden*

⁴*National Institute of Informatics, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo, 101-8430, Japan*

⁵*JST, ERATO, Kawarabayashi Large Graph Project,
2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo, 101-8430, Japan*





Reading notes:

- ▶ If you are not familiar with it, pay attention to the SIR model

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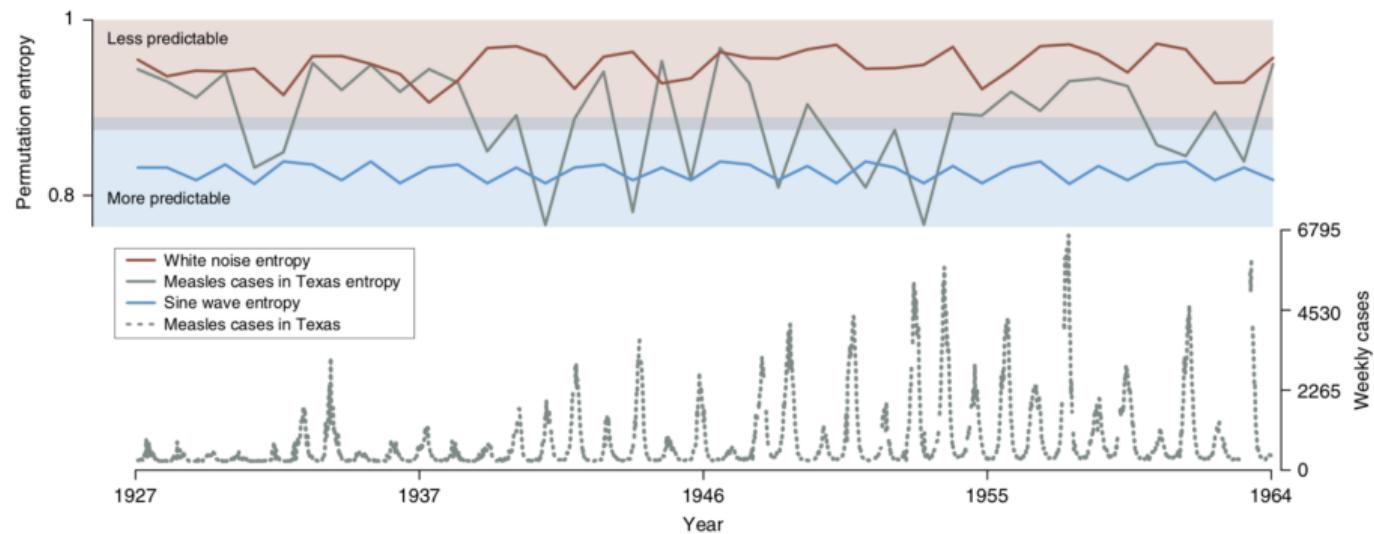
- ▶ If you are not familiar with it, pay attention to the SIR model
- ▶ Try to think about how this compares to other articles that we've read so far
(e.g., Cheng et al's work on cascade prediction and the MusicLab experiments by Salganik et al)

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- ▶ Try to think about how this compares to other articles that we've read so far (e.g., Cheng et al's work on cascade prediction and the MusicLab experiments by Salganik et al)
- ▶ Don't worry too much about the details of any specific claim. Focus on the big picture.

On the predictability of infectious disease outbreaks

Samuel V. Scarpino^{1,2,3,4,5,6} & Giovanni Petri^{6,7}



Permutation Entropy: A Natural Complexity Measure for Time Series

Christoph Bandt and Bernd Pompe

Institute of Mathematics and Institute of Physics, University of Greifswald, Greifswald, Germany
(Received 19 June 2001; revised manuscript received 20 December 2001; published 11 April 2002)

We introduce complexity parameters for time series based on comparison of neighboring values. The definition directly applies to arbitrary real-world data. For some well-known chaotic dynamical systems it is shown that our complexity behaves similar to Lyapunov exponents, and is particularly useful in the presence of dynamical or observational noise. The advantages of our method are its simplicity, extremely fast calculation, robustness, and invariance with respect to nonlinear monotonous transformations.

Example (from Bandt and Pompe, 2002): $x = 4, 7, 9, 10, 6, 11, 3$

- ▶ 4 pairs for which $x_t < x_{t+1}$, represent these as 01

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Permutation entropy order $n = 2$ as a measure of the probabilities of the permutations 01 and 10:

$$H(2) = -(4/6)\log_2(4/6) - (2/6)\log_2(2/6) \approx 0.918$$

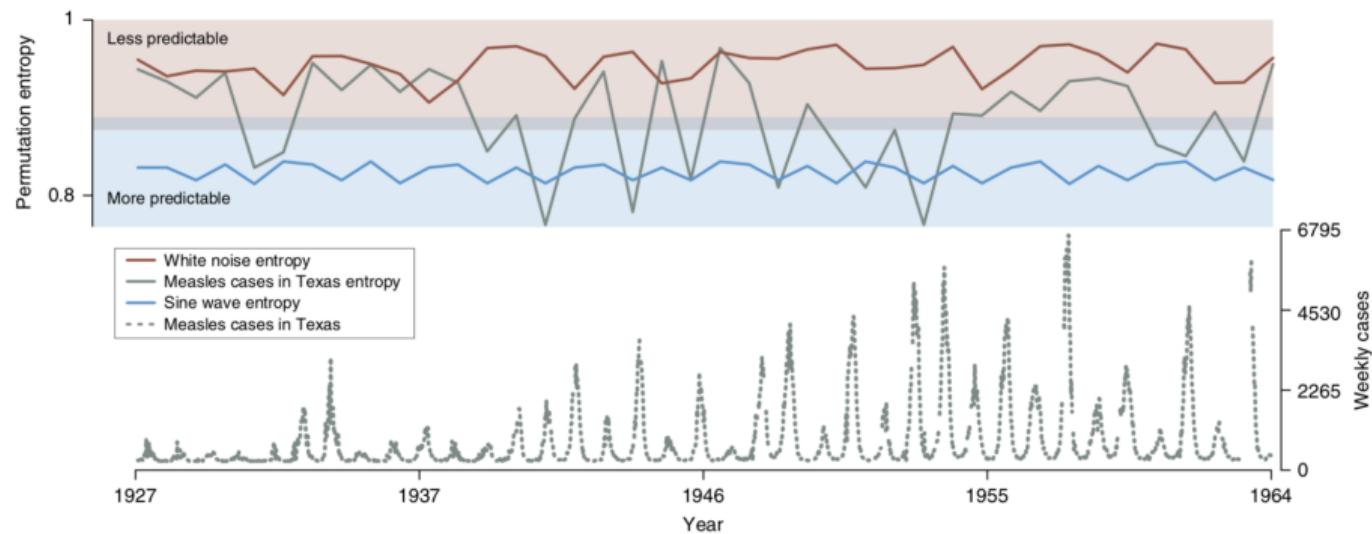
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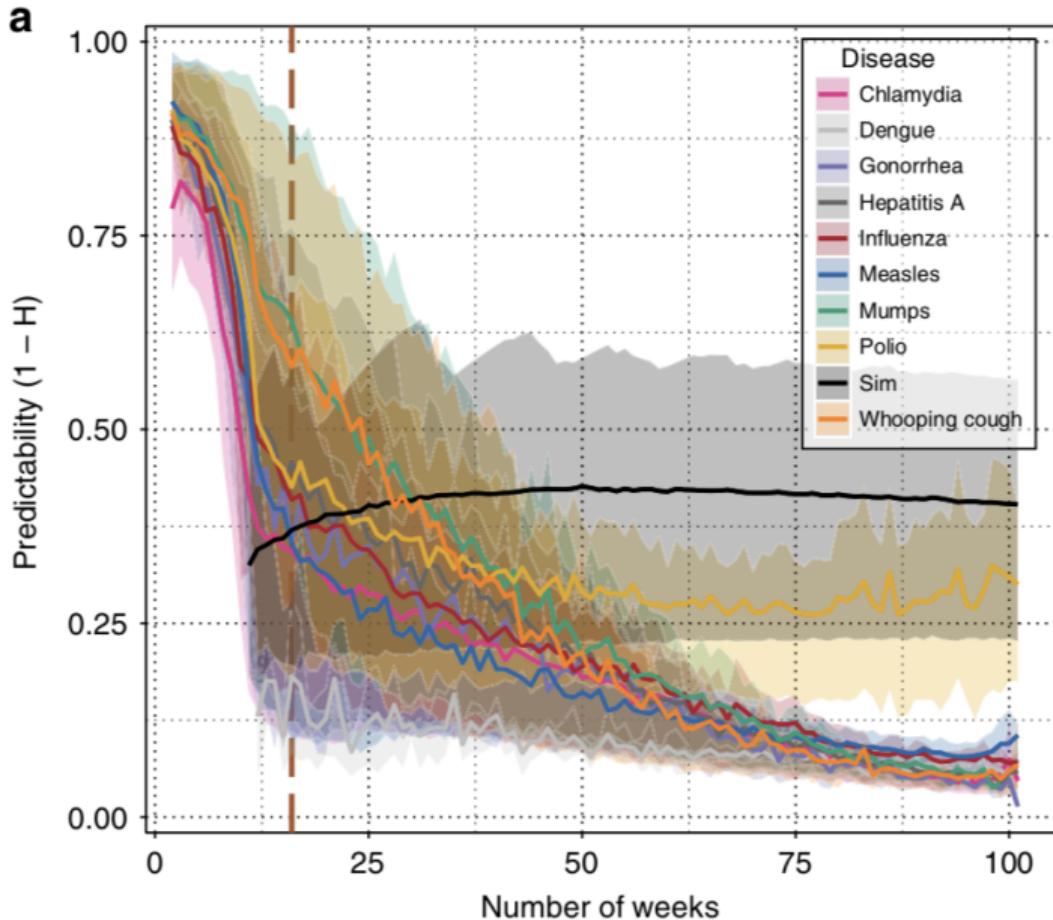
Next, we compare 3 consecutive values:

- ▶ $(4, 7, 9)$ and $(7, 9, 10)$ represent the permutation 012
- ▶ $(9, 10, 6)$ and $(6, 11, 3)$ correspond to the permutation 201 since
 $x_{t+2} < x_t < x_{t+1}$
- ▶ $(10, 6, 11)$ has the permutation type 102 since $x_{t+1} < x_t < x_{t+2}$

The permutation entropy of order $n = 3$:

$$H(3) = -(2/5)\log_2(2/5) - (2/5)\log_2(2/5) - (1/5)\log_2(1/5) \approx 1.512$$





Reading notes:

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Pandemics: spend
on surveillance,
not prediction

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