

# Quantum statistical complexity

Sharpening Occam's razor with quantum  
mechanics

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# Outline

1. How to define complexity
2. How to measure complexity
3. Using quantum mechanics to model a complex system
4. Connecting complexity to physical theories



1. How to define complexity



# General definition

“This leads us to the following tentative definition of complexity: A complex system is an ensemble of many similar elements which are interacting in a disordered way, resulting in robust organisation and memory.”

From “What is a complex system”, J Ladyman, J Lambert, K Wiesner (2010), <http://www.maths.bristol.ac.uk/~enxkw/Publications.html>



## 2. How to measure complexity



# Data-driven definition

Since statistical complexity is a measure applied to data, we offer the quantitative definition of a complex system:

“A system is complex if it can generate data series with high statistical complexity.”

From “What is a complex system”, J Ladyman, J Lambert, K Wiesner (2010), <http://www.maths.bristol.ac.uk/~enxkw/Publications.html>



# Information-theoretic measures of complexity

Take an infinite sequence of random variables  $X_{-\infty}^{\infty}$ , drawn according to a probability distribution  $P(X_{-\infty}^{\infty})$  (not necessarily i.i.d) (stationary process).

**Effective measure complexity** (Grassberger, Int. J. Theor. Phys. 9 (1986) 907-938):

$$EMC = \sum_{N=0}^{\infty} (h^N - h)$$

**Excess entropy** (Crutchfield, Feldman, Chaos 13 (2003) 25-54):

$$\mathbf{E} = \lim_{N \rightarrow \infty} I(X_{-N}^{-1}; X_0^N)$$

The two measures are equivalent:

$$EMC = \mathbf{E}$$



# Grouping strings into equivalence classes

Identify finite set of equivalence classes, obeying

$$\eta(x^n) = \{y^m : Pr(z^l|y^m) = Pr(z^l|x^n) \forall l\}$$

$$S_0 = \{3141592, 5926535, \dots\}$$

$$S_1 = \{4159265, \dots\}$$

...



# Statistical complexity

This set of equivalence classes is a “sufficient statistic” for the process, called “causal states” (Shalizi, Crutchfield. J. Stat. Phys. (2001) 104, 817-879).

The Statistical Complexity is the Shannon entropy over the stationary distribution of effective (causal) states:

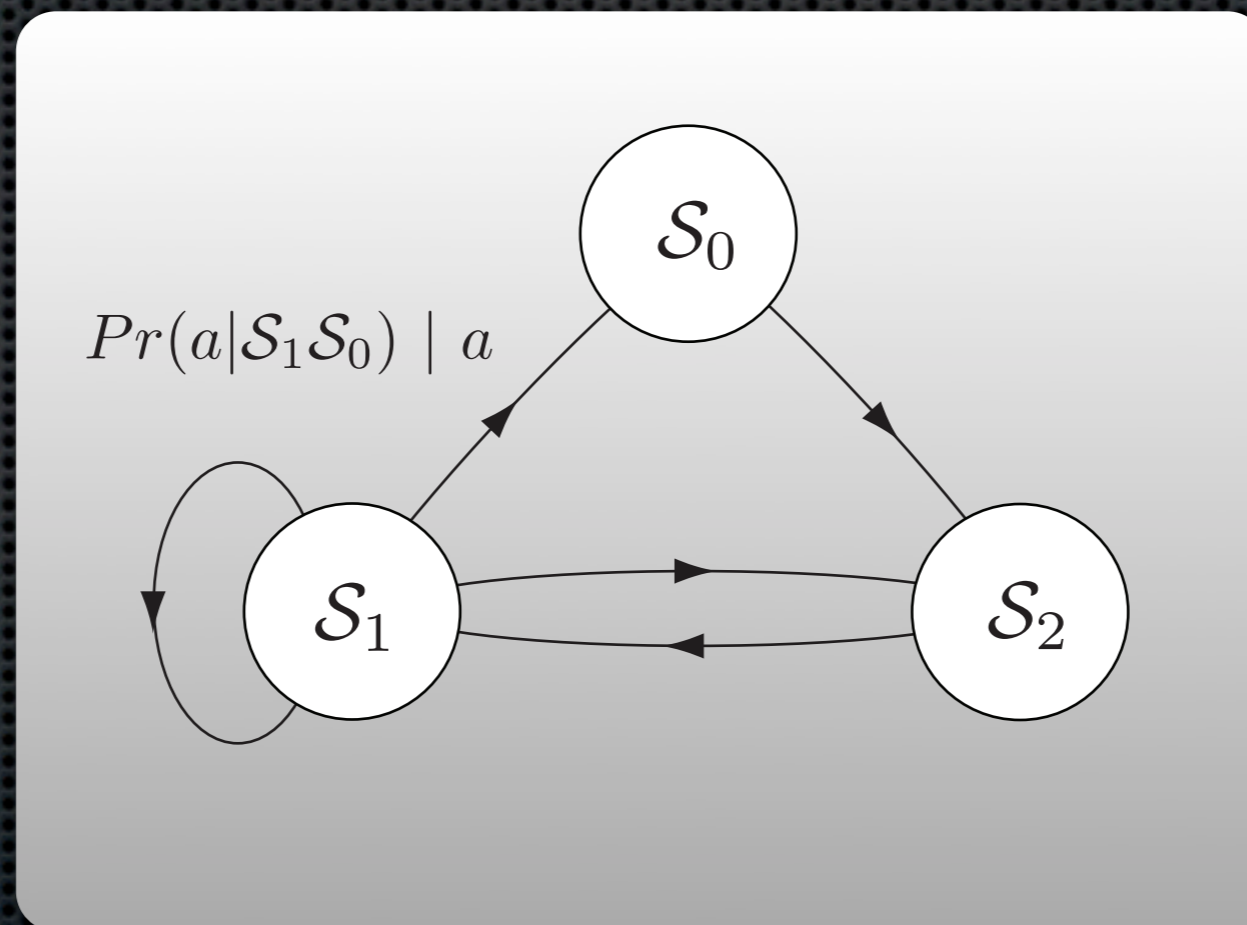
$$C_{\mu} = H(\mathcal{S})$$

The **Statistical Complexity** is the minimum amount of information needed to optimally predict a process.



# Minimal and optimal - Constructing an automaton

The resulting automaton / hidden Markov model is called ***e-machine***. It is the unique, minimal, optimal predictor (Shalizi, Crutchfield. J. Stat. Phys. (2001) 104, 817-879)





# Applications of statistical complexity

- Dynamical systems (Crutchfield, J.P. & Young, K. Inferring statistical complexity. Phys. Rev. Lett. 63, 105(1989).)
- Spin systems (Crutchfield, J.P. & Feldman, D.P. Statistical complexity of simple one-dimensional spin systems . Phys. Rev. E 55, R1239(1997).)
- Crystal growth (Varn, D.P., Canright, G.S. & Crutchfield, J.P. Discovering planar disorder in close-packed structures from x-ray diffraction: Beyond the fault model. Phys. Rev. B 66, 174110(2002).)
- Molecular dynamics (Li, C., Yang, H. & Komatsuzaki, T. Multiscale complex network of protein conformational fluctuations in single-molecule time series. Proceedings of the National Academy of Sciences 105, 536-541 (2008). D. Kelly et al. Inferring hidden Markov models from noisy time sequences. arXiv:1011.2969)
- Atmospheric turbulence (A. J. Palmer, C. W. Fairall, and W. A. Brewer, Complexity in the Atmosphere , IEEE Transactions on Geoscience and Remote Sensing 38, July 4 (2000).)
- Population dynamics (Crutchfield, J.P. & Görnerup, O. Objects that make objects: the population dynamics of structural complexity. Journal of the Royal Society Interface 22, 345-349(2006). Görnerup, O. & Crutchfield, J.P. Hierarchical Self-Organization in the Finitary Process Soup. Artificial Life 14, 245-254(2008).)
- Self-organisation (Shalizi, C.R., Shalizi, K.L. & Haslinger, R. Quantifying Self-Organization with Optimal Predictors. Phys. Rev. Lett. 93, 118701(2004).)
- Neural spike sequences (Tino, P. & Koteles, M. Extracting finite-state representations from recurrent neural networks trained on chaotic symbolic sequences. Neural Networks, IEEE Transactions on 10, 284-302(1999).)



# “Occam’s razor”

“Plurality is not to be posited without necessity.”



3. Using quantum-mechanics to model a complex system



# Room for improvement

“Given a stochastic process  $P (X_{-\infty}^{\infty})$  with excess entropy  $E$  and statistical complexity  $C_{\mu}$ . Let its corresponding  $\varepsilon$ -machine have transition probabilities  $T_{i,j}^{(r)}$ . Then  $C_{\mu} > E$  iff there exists a non-zero probability that two different causal states,  $S_j$  and  $S_k$  will both make a transition to a coinciding causal state  $S_l$  upon emission of a coinciding output  $r \in \Sigma$ , i.e.

$$T_{j,l}^{(r)}, T_{k,l}^{(r)} \neq 0 \quad “$$

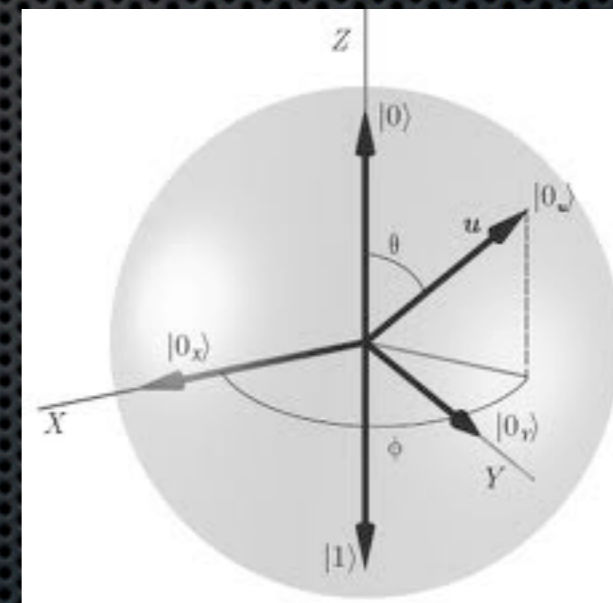
(Wiesner et al. arxiv:0905.2918. Gu, Wiesner et al. 2010)



# Quantum mechanical state

Classical bit vs quantum  
bit (qubit)

$$|\psi\rangle = c_1|0\rangle + c_2|1\rangle$$



[cqed.org](http://cqed.org)



# Quantum ‘causal state’\*

Alphabet  $\mathcal{A}$ , transition probabilities  $T_{jk}$ , causal states  $S_j$

Form a new, ‘quantum’ causal states:

$$|S_j\rangle = \sum_{k=1}^n \sum_{r \in \mathcal{A}} \sqrt{T_{jk}^{(r)}} |r\rangle |k\rangle$$

square roots of transition probabilities

basis set from causal states

basis set from alphabet

\* The term causal state is strictly speaking not accurate since minimality has not been proven.



# Quantum statistical complexity

Define ‘quantum statistical complexity’  $C_q$  as

$$C_q = -\text{Tr} \rho \log \rho$$

where  $\rho$  is the density matrix over quantum ‘causal states’.

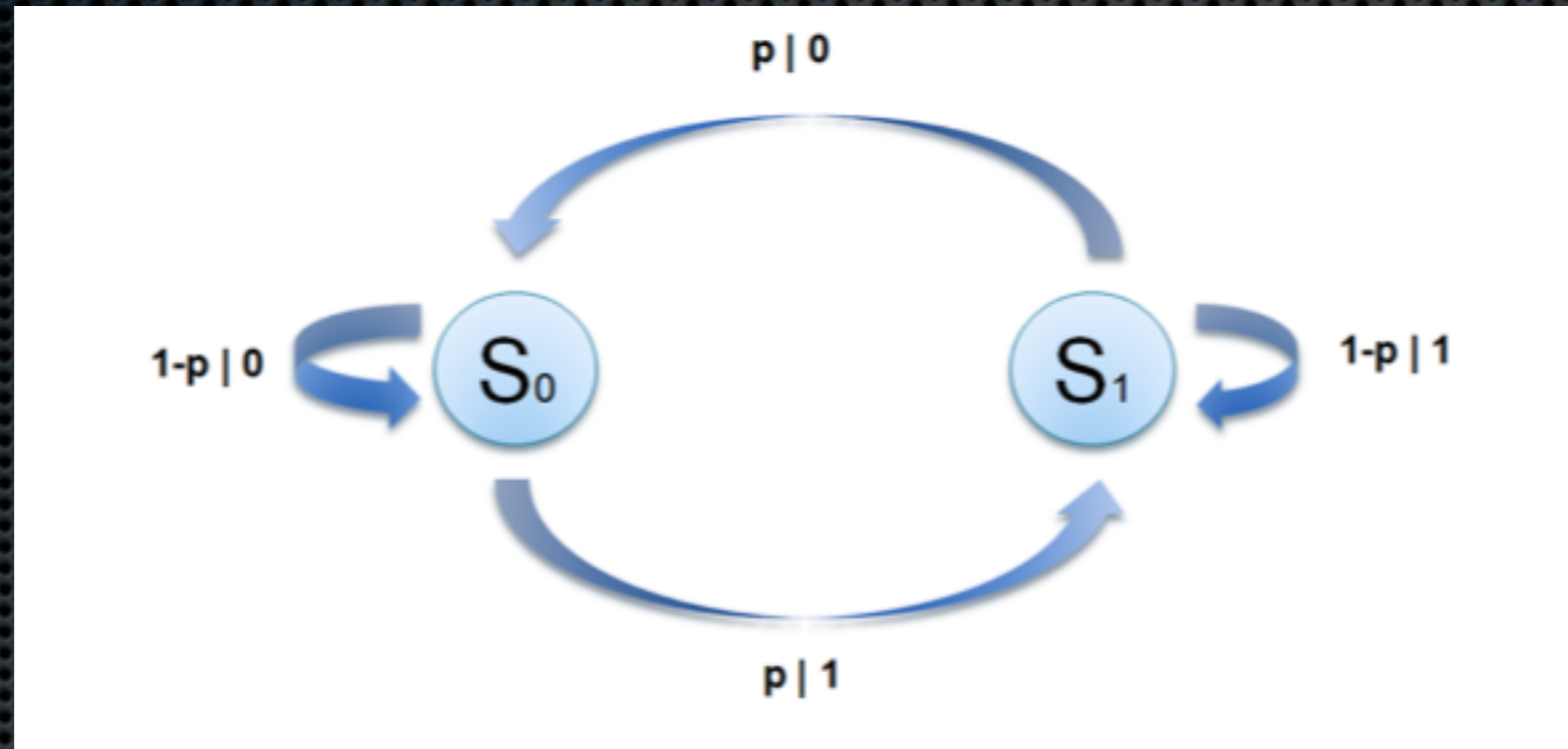


# Quantum statistical complexity

“Consider any stochastic process  $P(X_{-\infty}^{\infty})$  with excess entropy  $E$ , and that the optimal classical system that generates such statistics has entropy  $C_{\mu} > E$ . Then we may construct a quantum system that exhibits identical statistics, with internal entropy  $C_q < C_{\mu}$ .”



# Example: Biased flip

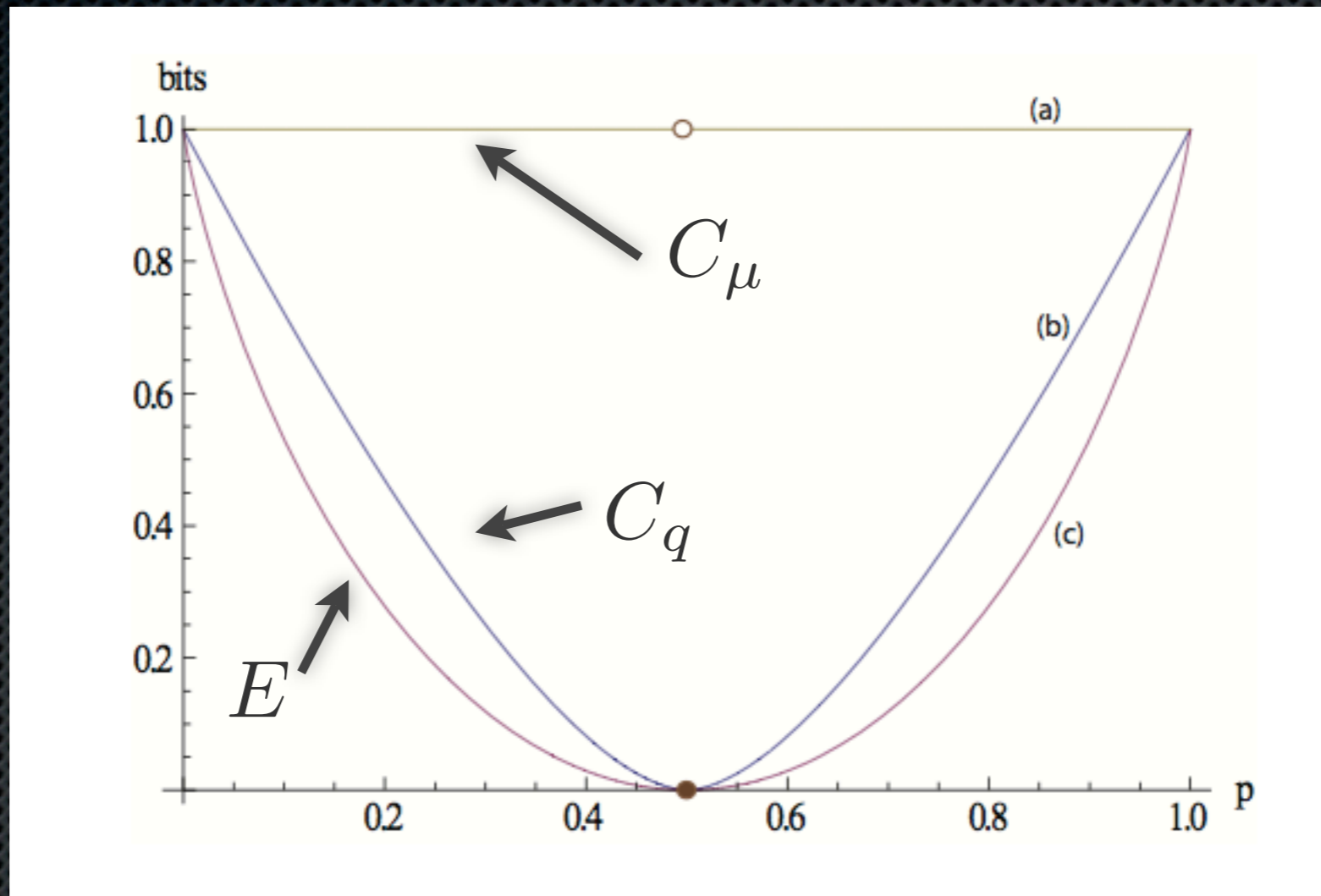


$$|S_A\rangle = \sqrt{p}|1\rangle|B\rangle + \sqrt{(1-p)}|0\rangle|A\rangle$$

$$|S_B\rangle = \sqrt{p}|0\rangle|A\rangle + \sqrt{(1-p)}|1\rangle|B\rangle$$



# Quantum beats classical



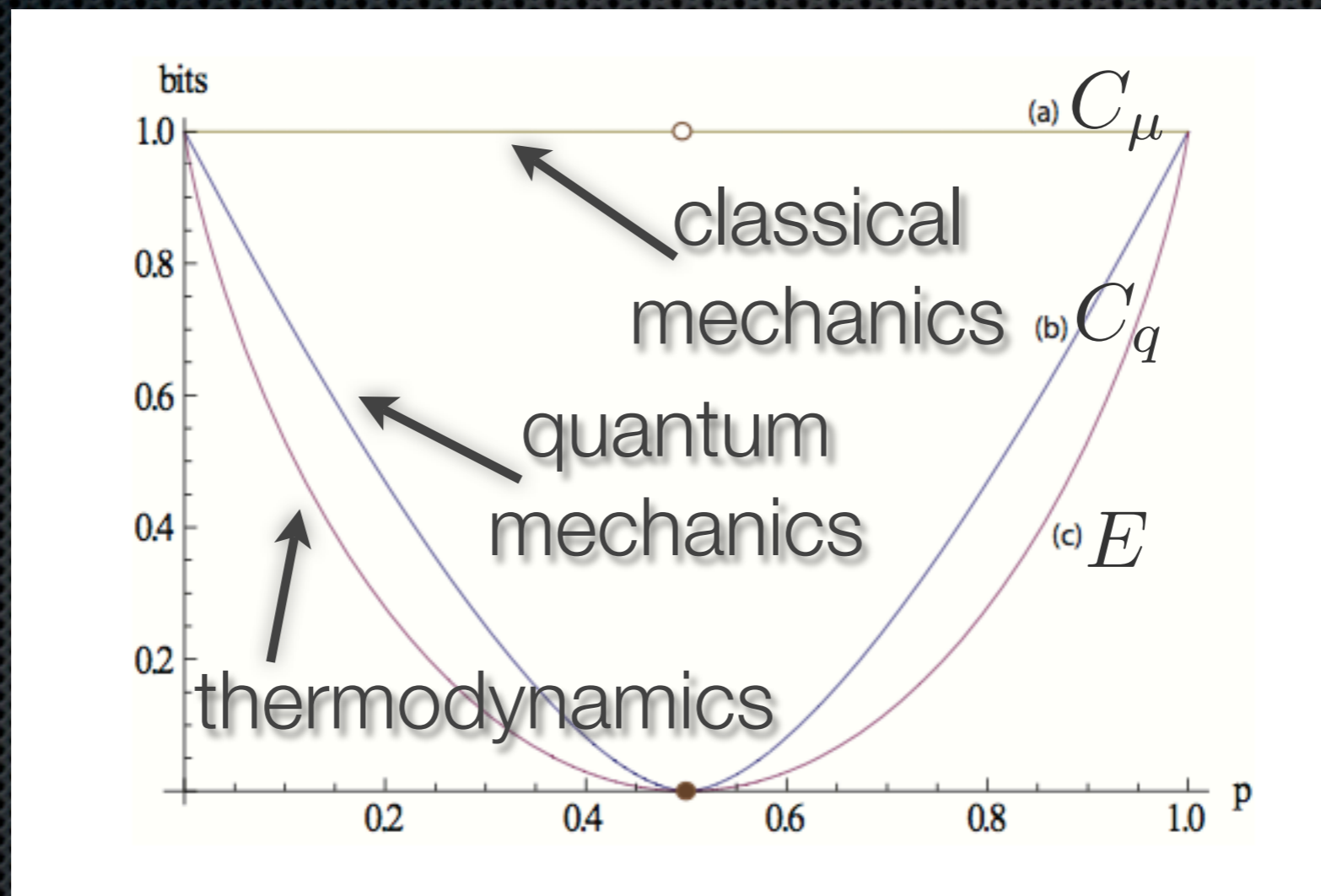
Following Occam we would favour the quantum model over the classical model.



# 4. Connecting complexity to physical theories



# Thermodynamic limit



Wiesner et al. arxiv:0905.2918.



# Conclusion

**Complexity:** A system is complex if it can generate data series with high statistical complexity.

**Occam's quantum razor:** We may construct a quantum system that exhibits identical statistics, with complexity  $C_q < C_\mu$ .

**Physical theories:** Complexity measures can be imbedded in existing physical theories.