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Reading reflections: Week 6
STAT/CS 387

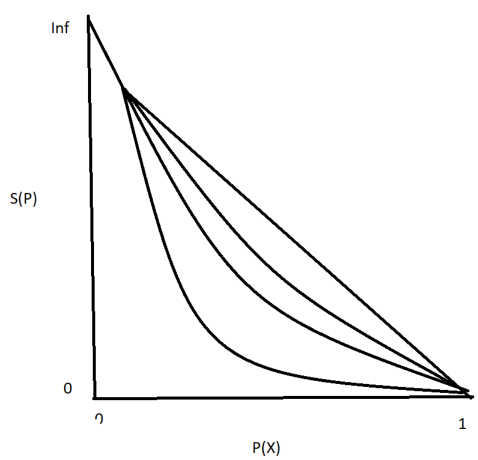
Title(s) read

- Measuring Information Transfer
- Detecting Causality in Complex Ecosystems

Reflection

In the last lecture of class, we discussed the intuition behind quantifying information gained from an observation, specifically the metric of entropy. We couldn't quite define what information is, but we could discuss what information does. Information reduces uncertainty. In Shannon's mathematical definition of entropy, uncertainty is measured by randomness. We want to start asking how surprised we are by the result of an observed process, say the roll of a die. Something that really helped me intuit the relationship between probability of a result and its "surprise" is the cartoon graph shown in class:

Figure 1: Surprise vs. Probability Cartoon



Now, entropy can be used as a summary statistic for a sample of observations. The Shannon Entropy discussed in class tells us the minimum number of bits required to represent a string or sequence of symbols. To satisfy the cartoon pmf like graph, Shannons Entropy is the negative log of the pmf of a data set. This way, when we see a symbol that has a lower probability of occurring, the event of the symbols occurrence carries more information.

The first paper, "Measuring Information Transfer", derives a new conditional form of entropy coined "transfer entropy" that is intended to separate "driving and responding elements" and to detect differences in coordination of subsystems. With respect to time series observations, this paper hopes to investigate a method to quantify the rate at which components of a structure exchange information. In the past, measures such as "mutual information" have been used for this purpose, however the authors claim that this metric does not include dynamical or directional information. Mutual information measures how much one variable tells us about another. In the context of entropy, this can be thought of as the reduction in uncertainty about one random variable given knowledge of another random variable. The paper rephrases the mutual information as a measure of deviation from independence of two processes. This study prepossess a time lag in either one of the variables being compared in order to give the flow of information a direction. They give an interesting example of this new metric being applied to show that in coupled heart rate, breath rate bi-variate data set, there is a stronger information transfer going from heart rate to breath rate than the other way around. Transfer Entropy is defined mathematically for process J and I as:

$\mathrm{T}_{J->I} = \sum p(i_{n+1}, i_n, ..., i_{n-k+1}, j_n) log(\frac{(p i_{n+1}|i_n,...,i_{n-k+1},j_n)}{i_{n+1}|i_n,...,i_{n-k+1}})$ If there is no flow of information from J to I, then the state of J has no influence on changes in I. In this case, in the mathematical expression, the logarithm term cancels and $T_{J->I} -> 0$. In the alternative, $T_{J->I} > 0$.

Detecting Causality in Complex Ecosystems proposes a model to identify causal networks and in particular distinguish causality from correlation in complex and even chaotic relationships. Over time, coupled variables can reverse association or decouple which motivates a flexible model building framework. In the past, Granger Causality has been used to replace correlation with predictability to indicate causation between variables. However, Granger Causality can produce unclear results if "weak to moderate" coupling is present, additionally, it is constrained to a purely stochastic world. The paper attempts to propose methods that address inseparable systems, identify weekly coupled variables and distinguish interactions among species from the effects of shared driving variables. They title this method "Convergent Cross Mapping" (CMM) which tests for causation by measuring the extent to which the historical records of Y can correctly predict X. CMM is said to looks for the signature of X in Y's time series by looking for collections of points in the attractor manifold of Y and a points in the X manifold where the two manifolds are built from lagges coordinates of the time series variables Y and X. If you can predict X from Y, then there is said to be a causal relationship. An important constraint of this method is that CMM only predicts states across variables and cannot forecast how systems evolve over time. There is a serious data requirement in order to give the systems cross mapping series a chance to converge. Thus the captured time window must be sufficiently long.