Information theory and statistical predictability Part II:Applications

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Some relevant references

Y. Tang, R. Kleeman, and A.M. Moore. On the reliability of ENSO dynamical predictions. *J. Atmos Sci*, **62**:1770-1791, 2005.

R. Kleeman. Limits, variability and general behaviour of statistical predictability of the mid-latitude atmosphere. *J. Atmos Sci*, **65**:263-275, 2008.

More complex models

Average Skill first 12 months (1971-94)



The interpretation of the two components of the simple model from the first Lecture as the first two EOFs of upper ocean heat content suggests using the amplitude of these two as a diagnostic of ENSO skill. In fact it works well in many coupled models I have examined. An example intermediate model is to the left. Notice it only works for anomaly correlation skill because only that skill measure includes the utility signal effect.



The simple stochastic model suggests that the signal part of Gaussian utility may be the dominant influence over variations in this quantity from initial condition to initial condition. Again this has been confirmed by examining several coupled models. At left is an example from the stochastically forced coupled model looked at in Lecture 1 and used in the summer school.

More complex models



Preliminary conclusions

• Evidence has been presented that a major factor in determining the variation of predictability of ENSO is variation in a quantity called "signal". In concrete terms this represents the amplitude of the first two EOFs of upper ocean heat content. This amplitude can show considerable variation from prediction to prediction and reflects not just warm/cold event magnitude (the first EOF) but also the classical Wyrtki buildup (the second EOF).

• This picture of predictability variation is in strong contrast to that usually advocated for weather prediction. In that case it is argued that variations in ensemble spread (which are caused by variations in flow instability) are responsible for skill variations. In terms of the formalism for utility introduced above that amounts to "dispersion" dominating utility variation.

• What about predictability in other interesting dynamical systems?

Predictability in other systems

• The classical dynamical system first introduced by Ed Lorenz is a 3 dimensional system exhibiting chaos. I checked that systems predictability and found that variations in dispersion were much more important than signal to utility variation at least for short range predictions. This result is perhaps the origin of the focus on skill spread relations in weather prediction.

• The case of mid-latitude atmospheric ENSO prediction has been examined in a series of recent papers by Arun Kumar and co-workers from NCEP. They find that global variations in ensemble <u>means</u> are much more strongly tied to ENSO SST variations than are variations in ensemble <u>spread</u>. Thus variations in the utility of such ENSO predictions is primarily due to the signal rather than the dispersion.

• Weather predictions are of course made in much more complex systems than that of Lorenz. What happens there?

Lorenz Chaotic Oscillator



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We use a reasonable resolution model the global atmosphere which of simulates well the mid-latitude mean state and eddies (storms). The model excludes moist convection for which no fully satisfactory representation yet exists. It also excludes radiation effects for computational speed. The forgoing effects are included using a simple "Newtonian" relaxation to a suitable (spatially varying) temperature profile. Models such as this are commonly called Held-Suarez dynamical cores. The model includes orography and is run in Northern winter mode.

We use a similar Gaussian intialization strategy to construct ensembles.

Mean Zonal (E-W) Wind at 300mb



Zonal Velocity Variance at 900mb



Technical Aspects

• To make the problem tractable we consider the reduced state space consisting of the first 100 EOFs of primitive equation prognostic variables (vorticity, divergence, temperature and surface pressure).

• Empirically prediction ensembles that are sampled from a Gaussian initial condition distribution remain approximately Gaussian for many weeks. We thus use the analytical Gaussian formulae for entropy.

• We use a crude Gaussian initial condition distribution intended to simulate a coarse resolution observing network. The spread of the distribution is an order of magnitude smaller than that of the climatological distribution.

• We used a horizontal resolution of T42 and vertical resolution of 5 levels but tested robustness of results using T85. The standard resolution is around 3 degrees in latitude and longitude.



A typical relaxation is shown. It exhibits a sharp "cutoff" at around 40 days. Results are highly robust to details of calculation. The right panel is from a model version with double the horizontal resolution of the left panel. Incomplete convergence on the left is due to sampling error since ensembles are smaller in this case.



One can study the relaxation process regionally as well as globally. Winter storm track regions exhibit much more rapid (and more linear) relaxation than summer regions. The winter results dominate the global results since they account for most of the variability within the total system. Temporary increases in relative entropy are due to information flow from one region to another.



Variation of relative entropy with initial condition is dominated by the signal component particularly at short skillful prediction times. This result is a variance with conventional wisdom in operational weather prediction which asserts that there should exist a strong relationship between predictability and spread of ensembles. In this respect the atmosphere appears to resemble more closely our initial ENSO simple stochastic rather than the simple Lorenz chaotic model.

Nature of Signal and Dispersion



Signal shows little preference for any particular EOF and seems to be simply a generic anomalous pattern present in the prediction ensemble. Dispersion shows more such preference but this has not been thoroughly analysed yet. Both dispersion and signal show strong temporal decorrelation over 2-5 days suggesting that the patterns responsible for high or low predictability "dissipate" rather rapidly. Note that longer lag correlations appear stronger for long range predictions. The general kind of behaviour reported here seems different to climate prediction where relatively few EOF modes appear responsible for signal (and predictability).