From MOS to eMOS
Generalising Model Output Statistics for Full Ensemble Forecasts

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Introduction

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Given: *only* the model-wet/dry event
(whether model-precip is more or less than 0mm)

Forecast: probability of precip > 0mm in an actual rain gauge.
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  1. Direct interpretation; model-precip and weather-precip are treated as identical. The forecast probability for real-precip is the proportion of model-wet events in the ensemble.
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  2. Scenario MOS; a separate forecast probability is made for each ensemble member. These are then combined.
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  3. Ensemble MOS (eMOS); the forecast is a function of the joint distribution of the *whole* ensemble.
• Ignorance is $-\log f(x)$, where $f(x)$ is the forecast probability of the outcome $x$. Smaller ignorance relative to climatology or another forecast is better.
• The confidence intervals are $\pm 1$ bootstrap std. dev.
Ensemble members are interpreted as equally plausible scenarios:

1. For each ensemble member (model-wet/dry) a probability forecast scenario is created. For example:
   - model-wet could correspond to a 50% chance of precip (and, of course, 50% chance of no precip),
   - model-dry corresponds to a 5% chance of precip (and 95% chance of no precip).

   These actual percentages chosen are the parameters of our scenario MOS.

2. The forecast is the average of all the scenarios.

3. The parameters are tuned to minimise the forecast's ignorance on a historical data-set.
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In contrast to the direct interpretation, performance is now better than climatology.

Skill generally improves with shorter lead times.
Idea: ensemble MOS

Any forecast method is a function from the ensemble to the forecast probability:

Scenario MOS:

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\text{Ensemble} \xrightarrow{\text{MOS}} \text{Scenarios} \xrightarrow{\text{Combine}} \text{Forecast}
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- Going through the intermediate stage of a scenario forecast corresponding to each ensemble member can be a strong constraint on the types of forecast functions possible.
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- Any forecast method is just a function from \#wet to the probability of precip:

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c|c|c}
#Wet & 0 & 10 & 20 & 30 & 40 & 50 \\
\hline
\text{Probability of precip} & 0 & 0.1 & 0.2 & 0.3 & 0.4 & 0.5 \\
\end{array}
\]

Direct interpretation is, essentially, the identity.
Simplified Example: eMOS

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Any forecast method is just a function from \#wet to the probability of precip:

An eMOS method can choose a non-linear predictor.
Simplified Example: eMOS

- The method of analogues can be used to fit the eMOS function:

Predicted probability of precip is the proportion of historical cases with precip at nearby #wet values.
• Interpreting the ensemble as a whole leads to significant improvements in skill over scenarios in the 1–7 day range.
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• This is clearly seen by comparing the two models directly rather than to climatology.
Generalising to more complete information

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- But now the ensemble cannot be described by a single quantity like #wet. (But it may contain more information.) Instead, we now have a *distribution* of model-precip.

- Can summarise the distribution by (say) its 10%, 50%, and 90% quantiles ($p_{10}$, $p_{50}$, and $p_{90}$). And fit a function from this information into the probability of real precipitation:

  \[(p_{10}, p_{50}, p_{90}) \mapsto \text{probability of real precip}\]
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- As the threshold increases, skill over climatology decreases.
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More information on the diagram:
- The chart compares quantile eMOS vs. Climatology for precipitation above 2mm.
- The y-axis represents ignorance in bits, ranging from -0.6 to 0.
- The x-axis represents leadtime in days, ranging from 0 to 10.

The chart shows a downward trend, indicating a decrease in skill over time.
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  • Ensemble-spread is not forecast-uncertainty.
• Forecast-verification archives of sufficient size are essential.
• eMOS makes no strong assumptions about the “meaning” of the information it uses — it can be easily extended to combine information from different sources.