STATISTICAL PREDICTION OF ASTRONOMICAL SEEING
& OF TELESCOPE THERMAL ENVIRONMENT

F. Murtagh (1), M. Sarazin (2) and H.-M. Adorf (3)

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(1) Space Telescope – European Coordinating Facility, European Southern Observatory. Affiliated to Astrophysics Div., Space Science Dept., European Space Agency.

(2) European Southern Observatory.

(3) Space Telescope – European Coordinating Facility, European Southern Observatory.

INTRODUCTION

Weather conditions on Cerro Paranal have been under investigation since 1982. By late 1987, a monitoring station had been set up to continuously track the evolution of meteorological and atmospheric variables[1]. On-line seeing monitors based on the measurement of differential image motion were specially designed for this monitoring activity. Data collected are summarized in quarterly meteorological reports.

Two studies are currently being undertaken, for later incorporation into the envisaged VLT Astronomical Weather Station. These relate to (i) 24-hour advance temperature prediction, which would permit air conditioning in the telescope enclosure to be preset as a function of the next night's minimum expected temperature; and (ii) prediction of seeing, a few hours in advance, to allow flexible scheduling of the most appropriate instrumentation.

The data used in this assessment relate to over 18000 observations carried out in austral summer 1989-1990. Many missing values, and the relative utility of the different variables, required extensive initial exploration in order to arrive at data-sets on which to carry out assessments.

DATA PREPROCESSING: TEMPERATURE

The following sets of tuples were derived from this data, for temperature prediction:

$$t_n, t_{n-1}, t_{n-2}, t_{n-3}, p_{n-1}, p_{n-2}$$

where

- t_n is the temperature value to be predicted;
- $t_{n-1}, t_{n-2}, t_{n-3}$ are temperature values at $n-24$, $n-48$, and $n-72$ hours;

[1] M. Sarazin, "ESO site evaluation for the VLT", in F. Sanchez and M. Vazquez (Eds.), *New Windows to the Universe*, Vol. 1, Cambridge, New York, 1990, 435–439.

• p_{n-1}, p_{n-2} are pressure values at $n-24$ and $n-48$ hours.

The sequence of temperatures is used in order to capture contemporary trend. Pressure is used for its information on quickly changing weather conditions, such as incoming weather fronts.

Longer sequences of temperatures, alone, were also assessed, but not further reported on here. The number of tuples used in the results below, with no values missing, was 5260.

For production use, a characteristic of the data to be borne in mind is that it is constantly growing. The forecasting approach implemented must be able to cope with such a dynamic data set.

DATA PREPROCESSING: SEEING

A data fusion strategy, based on external meteorological data together with data from the ground meteorological station, is currently under consideration. If meteorological variables of interest can be forecast externally, then it may be possible to pose the problem of prediction of seeing as a nowcasting one; i.e. to compute future seeing conditions as a function of the predicted meteorological environment.

Nowcasting of seeing values was assessed, based on the following tuples:

$$fwhm, s_1, s_1dev, d_1, rh, t_1, p, \Delta s_1, \Delta t_1$$

where *fwhm* is the seeing (arcsec, full width at half max, at 5m above ground); $s1$ is the windspeed at 10m above ground; s_1dev is the standard deviation, in the averaging period, using samples at every 2s; $d1$ is the wind direction; and rh is the relative humidity. The Δ terms relate to differences with respect to the previous time step (i.e. 20 minutes previously). Some further variables were dropped from the analysis, since they were highly correlated with some of the above variables. The objective, therefore, was multiple regression of *fwhm* on the eight carrier variables above. We further considered this problem as a two-category classification one, as follows. "Good" seeing was defined as less than 0.6 arcsec, and "bad" above this. This threshold value was near the median of the seeing values.

The number of tuples, with missing values excluded, was 4440. All values were range-normalized (i.e. each variable was mapped linearly onto the interval $[0, 1]$). Results for nowcasting of good and bad seeing are given below.

PREDICTION METHOD

Prediction risk, i.e. expected performance on future data, is approximated by expected performance on the finite set of test data. A cross-validation mean squared error measure was used to estimate prediction risk. Various experiments were carried out either on all members of test sets, or alternatively on a randomized set of tuples uniformly sampled from the test set.

A "stock" of 4000 tuples was used for all temperature experiments, and predictions were carried out on the subpopulation of 1260 (chronologically late) tuples. A similar "stock" of 3000 tuples was used for the seeing experiments, and predictions were carried out on the subpopulation of 1440 (chronologically late) tuples.

Temperature prediction was carried out using a 1-nearest neighbor method. I.e. the best matching, chronologically prior, tuple was sought. The matching was carried out on the five independent variables in the tuple, i.e. $t_{n-1}, t_{n-2}, t_{n-3}, p_{n-1}, p_{n-2}$, each variable having been range-normalized to the interval $[0, 1]$, and using Euclidean distance. A new five-valued tuple was matched against all chronologically prior prototypes. The value of t_n corresponding to the best-matching prototype provided the forecast.

This may be viewed as seeking the series of temperatures and pressures, in the past, which is most similar to the given series of temperatures. Such a general approach is shared by traditional weather lore, and is also used in other fields. Implementation-wise, the relaxed model assumptions of this approach are of benefit, given that such a method would be incorporated into a constantly changing data environment, presenting additional practical difficulties such as missing data (due to technical or communication failures).

Apart from the nearest neighbor approach, a multilayer perceptron was also used for temperature prediction. The results for the latter are not quoted below since they were found to be worse than results yielded by the nearest neighbor approach. The reason for this may have been due to problems encountered by the weight estimation algorithm used (conjugate gradient): i.e. that local optima in weight space were arrived at. Clearly other techniques (e.g. nonlinear times series analysis) could be tried. The results presented below constitute a benchmark for future assessments.

Seeing prediction was carried out using 1-nearest neighbor, as above, and using a multilayer perceptron. In the case of the latter, results given below were obtained with an architecture consisting of 8 input units (allowing for the input of 8 meteorological variables, on the basis of which the predicted value was to be found), 2 output units (associated with good versus bad seeing), and 4 hidden layer units.

RESULTS

We begin with temperature (see Fig. 1 showing a sample of one-step-ahead prediction results, where a "step" represents 24 hours), and follow with seeing.

- Percentage of predicted temperature values within 2^o of actual value: 85.1%
- Percentage of predicted temperature values within 1^o of actual value: 74.3%
- Percentage of predicted temperature values within $.5^o$ of actual value: 62.3%

"Carbon-copy" temperature prediction (whereby the value of t_{n-1} was used as the forecast of t_n) for the random samples used gave considerably poorer results: for the 0.5^o case, this was 20.5%.

Using temperature values alone, and not pressure, had indicated improved results for 2^o prediction, but poorer results for 0.5^o prediction.

Figure 1: Observation sequence number plotted against temperature. Actual and predicted temperatures are superimposed (respectively: full line, and dotted line).

Predictability of large temperature changes (defined as $> 3^o$ difference) was also assessed in a similar way. The hit rate (a big change is correctly predicted, given that a large change actually takes place) was 67.6%. The false alarm rate (a large change is predicted, but does not ensue in reality) was 6.5%.

Nowcasting of seeing yielded the following results (20 min. averages). Using 1-nearest neighbor:

- Seeing hit rate (i.e. correctly forecasting good seeing): 75.1%
- Seeing false alarm rate (i.e. good seeing wrongly output): 35.1%

Using the multilayer perceptron, we obtained a seeing hit rate of 71.2%; and a seeing false alarm rate of 20.3%

DISCUSSION AND CONCLUSIONS

The use of temperatures at time intervals less than 24 hours in advance could be used to further improve on the prediction accuracy quoted. In fact, one could use temperatures up to about 6 hours from the time that one wishes a good prediction.

We aim to use predicted temperatures, and other parameters, to provide a predicted meteorological environment. The latter will then be used for nowcasting the seeing. Given that the dependent variables are inextricably related (cf. how we used pressure in predicting temperature, above), we will not seek to estimate accuracy of overall seeing prediction on the basis of accuracies of temperature prediction, and predictions of other mateorological variables. Instead, we will estimate the overall quality of seeing prediction on the basis of a test sample of known seeing values, just as was done for the results quoted above.

The results presented here provide a baseline, which alternative approaches may seek to improve on. Among such alternative approaches, we may mention nonlinear time series analysis, clusterwise regression[2], and parametric, Bayesian approaches[3]. The results given above are conservative: in practice, a larger "stock" of prototypes, corresponding to at least one full year, could be used. We found the multilayer perceptron (using conjugate gradient estimation of weights) algorithm to perform poorly in the temperature experiments, but acceptably well in the seeing experiments. The nearest neighbor approach, in spite of its known drawbacks[4], also performed well.

[2] F. Murtagh, "Approaches to multivariate nonparametric prediction", 16th Annual Meeting, Gesellschaft für Klassifikation, April 1992.

[3] H.-M. Adorf, "A note on Bayes prediction", internal report, April 1992.

[4] S. Geman, E. Bienenstock & R. Doursat, "Neural networks and the bias/variance dilemma", *Neural Computation* **4**, 1–58, 1992.