Classification of Meteorological Patterns

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Abstract

A classification system which organize in a restricted number typical meteorological situations, is useful in order to find a relationship between meteorological patterns present in the forecasts and derive local weather parameters. The conventional classifiers based on climatology commonly adopted by weather centres suffer from subjective construction and application which weak the analogy method. This paper deals with the construction of an artificial neural network aimed to classify meteorological patterns. Solutions to meteorological requirements are presented together with operational applications.

1 Introduction

The suitable classification technique should be based on an objective learning of a large set of meteorological situations. Once the learning performed, the classification of situations remains fixed. Climatological characteristics are then deduced from classified typical situations.

By introducing an artificial neural network, we attempt to design a system capable of collecting and organising information related to the features it has to analyse. By adopting an unsupervised learning, the network is expected to create categories from correlations contained in the input data, and to provide output signals corresponding to the input categories [1].

We select the Kohonen artificial neural network whose purpose is to cluster in the same categories similar features because of its so-called topological organisation [2]. In fact mapping features into categories with Kohonen network keeps a topological sense; two similar features will be mapped on two neighbouring areas of the network. A meteorological classification requires also a smooth transition between close classified situations in order to cluster on the network situations with similar main features.

Finally, graphical results presented to forecasters or climatologists must be of meteorological relevance. Thus, the required display of the resulting classification should be a two-dimensional chart, where each unit is a typical meteorological situation.

2 Meteorological context

Two meteorological fields are chosen to characterize the weather conditions; - the temperature at 850 hPa level and -the geopotential heights at 500 hPa level. These two fields are selected because they are uncoupled to the local ground phenomena we want to derive from the classification. Moreover, it can be said that a good confidence level for both fields is reached in forecasts obtained by numerical models.
Each field is defined by a 10x10 matrix of values located on a regular latitude/longitude grid. The data set contains 8000 analysed situations composed by 2 level patterns (from 1981 to 1996).

After the organisation of the network, a typical situation that has been learnt corresponds to each unit of the Kohonen chart and is represented by a two level matrix of its synaptic weights.

3 Kohonen artificial neural network

For our purpose, the Kohonen chart is composed of 12x12 units set on a map with toroidal topology which permits to avoid the accumulation of the most frequent patterns in the corners and on the edges.
In order to measure the learning process, the values of the Root Mean Square (RMS) distance between the elected units and presented fields are computed during and at the end of the learning phase. Season overfitting is prevented by destroying the chronological order of the input vector.
Normalisation of the input fields is not suitable because it introduces artificial gradients without any meteorological sense. Moreover, the resulting situations (defined by the synaptic weights of the units) are of few meteorological relevance. We have chosen to run the Kohonen classification on the input vector from which we subtracted the seasonal mean of each field. No further normalisation is applied on the input fields.
Fine tuning, such as the choice of the activation function and its free parameters, was performed in order to improve the recognition rate of situations from an independent data set. Our aim is not only a low average RMS distance on the evaluation data set, but also a good classification of seldom patterns.
In order to avoid large RMS distances between a presented situation and the corresponding elected unit, several techniques are tested. Sensible improvement is obtained by a favourised learning, which consists in suppressing frequently encounterd patterns and multiplying seldom ones during the learning process.

Topological mapping makes sense as closely related weather patterns appear to be located to close lying units (Fig. 1).

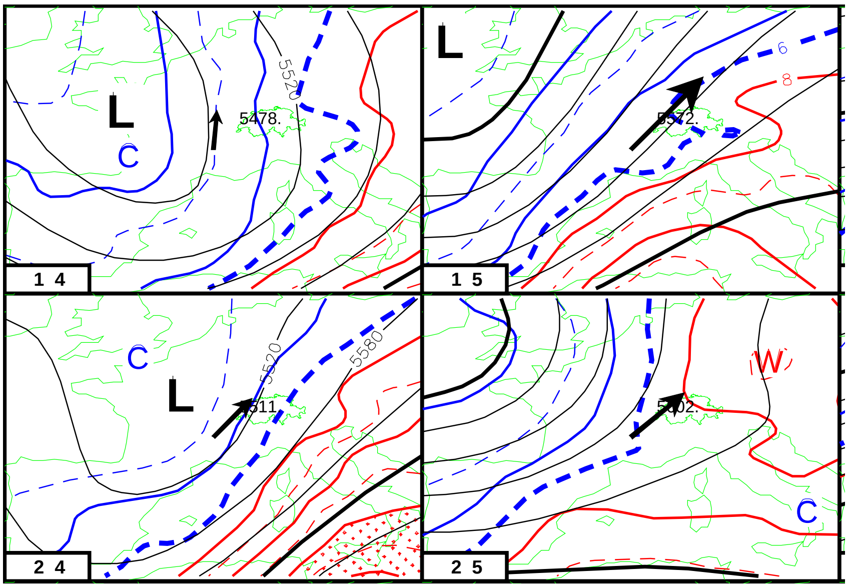

Fig. 1. Four units subset of the Kohonen chart representing the synaptic weights of the two levels, respectively the temperatures at 850 hPa and geopotential heights at 500 hPa. Characteristics of the neural network are: climatic seasonal mean field subtraction, no internal normalisation, 12x12 toroidal map of two levels, conic activation, 2000 input patterns and 100 loops.

4 Applications

4.1 Classification of ensemble forecasts

The basic idea of the Ensemble Prediction System (EPS) is that the analysis used in a numerical weather model is always an approximation of the reality. As the atmospheric system is known to be chaotic, the numerical forecast will deviate from real solution depending on the quality of the initial analysis [3][4].

The EPS is composed of 50 runs of the same model, with small perturbations on the initial state. This leads to a flood of data from which the sensitivity to the initial condition has to be evaluated in order to estimate the predictability of the atmosphere.

The members of EPS are classified within the 144 typical situations learnt by the neural network. By analysing the distribution of the elected units corresponding to each run (Fig. 2.a), the predictability can be objectively evaluated for example by measuring the order on the Kohonen map by means of entropy [7] (Fig. 2.b).

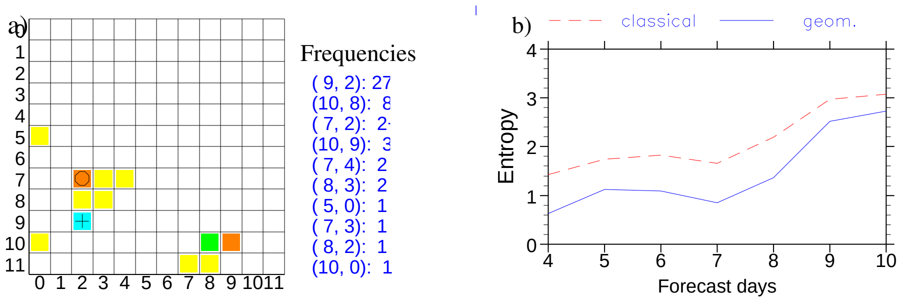

Fig. 2.a) Distribution of elected units on the Kohonen map, at the forecasting time day plus 7. **2.b)** Entropies as a function of forecasting time steps.

4.2 Probability of precipitation

Once the network is fixed, local weather parameters may be derived from the typical situations. Statistical relationships are computed between moderate to heavy precipitation (here the precipitation amount greater than 20 mm/day) and the units of the Kohonen chart.

Again the topology of the artificial neural network agrees to climatological requirements by grouping together the rainy situations on the map (Fig. 3).

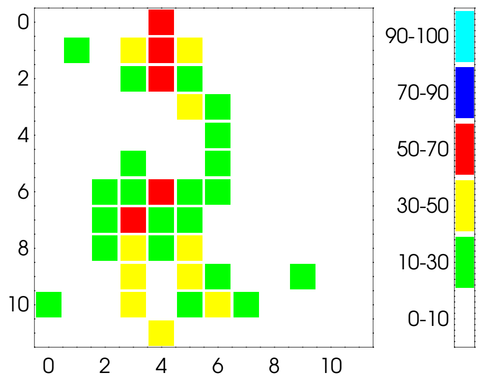

Fig. 3. Probability of precipitation (%) greater than 20 mm in 24 hours at Lugano/Switzerland, attributed to the units of the established Kohonen chart.

A verification of the probability of precipitation obtained by combining the distribution of EPS members on the Kohonen chart and the corresponding probability of precipitation leads to an important improvement of the forecast towards the direct model output.

5 Conclusion

The presented classification technique is adequate to meteorological patterns, because it conducts successfully a classification of typical weather situations. The applied Kohonen algorithms together with the chosen parameters have enhanced the resulting classification.

The Kohonen chart possesses the required meteorological relevance. Moreover the derived parameters (such as the local precipitation) associated to the network units show that climatological features are involved in the learnt typical situations. Therefore substantial improvement of local weather forecasts is reached by introducing the classification as post-processing of the numerical weather forecasts.

When a large set of runs are classified, the overview Kohonen chart of the whole network allows an intuitive estimation of predictability, assessed by a measure of entropy. Another useful application of such a meteorological classifier is to produce an objective verification tool of forecasted patterns.

References

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