Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence

Forecast Oriented Classification of Spatio-Temporal Extreme Events

Zhengzhang Chen[1,*], **Yusheng Xie**[1], **Yu Cheng**[1],**Kunpeng Zhang**[1],
Ankit Agrawal[1], **Wei-keng Liao**[1], **Nagiza F. Samatova**[2], **Alok Choudhary**[1]
[1]Northwestern University, Evanston 60208, IL, USA
[2]North Carolina State University, Raleigh 27695, NC, USA
[*]zhengzhang.chen@northwestern.edu

Abstract

In complex dynamic systems, accurate forecasting of extreme events, such as hurricanes, is a highly underdetermined, yet very important sustainability problem. While physics-based models deserve their own merits, they often provide unreliable predictions for variables highly related to extreme events. In this paper, we propose a new *supervised machine learning* problem, which we call a ***forecast oriented classification of spatio-temporal extreme events***. We formulate three important real-world extreme event classification tasks, including seasonal forecasting of (a) tropical cyclones in Northern Hemisphere, (b) hurricanes and landfalling hurricanes in North Atlantic, and (c) North African rainfall. Corresponding predictor and predictand data sets are constructed. These data present unique characteristics and challenges that could potentially motivate future Artificial Intelligent and Data Mining research.

1 Introduction

Accurate forecasting of extreme events, such as hurricanes, droughts and earthquakes, is a paramount priority for our society. Their adverse nature can change the landscape of society by triggering abrupt changes in the landscape around them, defined by their catastrophic characteristics. For example, in Western Africa, periods of very low relative humidity often coincide with higher incidences of meningitis epidemics that affects more than 200,000 people throughout the African Sahel region annually [Molesworth *et al.*, 2003]. Our ability to predict the occurrence of such events—ahead-of-time, with the lead-time of days, weeks, and even months—could translate to taking preventive measures to eliminate or reduce the severity of the event.

Fortunately, the occurrences of extreme events are relatively rare. For example, only 92 hurricanes of great destructive magnitude have been reported to strike the United States from 1851-2004. While the rarity of occurrence of these extreme events is a blessing in the real sense, it is a curse from a statistical machine learning perspective, given the lack of an appropriate number of observational events to build models upon. This issue becomes worse if the characteristics of these events come into consideration, as these events can occur in different locations and during different times of the year. Thus, considering the fact of having only a handful of available observational events ($m \approx 100$'s) in high-dimensional spaces ($n \approx 10,000$'s), the existing machine learning methods easily become hardly suitable for dealing with such *underdetermined, or unconstrained, problems* ($m << n$).

Presently, physics-based models and simulations from first-principles have been making relatively reliable predictions at global spatial scale for ancillary variables, such as climatological factors including Sea Surface Temperature, humidity profiles over land, or wind speed at different heights. However, they provide least reliable predictions for variables that are crucial for impact assessment for adverse extreme events including regional precipitation, hurricane intensity and frequency, droughts and floods. In fact, "The sad truth of climate science is that the most crucial information is the least reliable" [Schiermeier, 2010].

While physics-based approaches deserve their own merits, in this paper, we draw readers' attention to a different, yet complementary, *supervised machine learning* problem. Namely, given a historic record about rarely occurring spatio-temporal extreme events of interest, can an algorithm learn the complex linear and non-linear relationships between system parameters and the event's response variable, so that the algorithm can predict what phase the system will likely transition to in some future time and in some spatial region, given the knowledge about the system's parameters defined over global spatial scales before the event's occurrence? We call this problem a ***forecast oriented classification of spatio-temporal extreme events***.

We successfully model three real-world extreme event prediction tasks—seasonal extreme event forecasts of Northern Hemisphere tropical cyclone counts, North Atlantic landfalling hurricane counts, and Sahel rainfall intensity—as forecast oriented classification of spatio-temporal extreme events problems. And we construct corresponding predictor and predictand datasets and analyze their unique characteristics and challenges.

2 Problem Formulation

Three real-world extreme event prediction tasks are considered as motivating examples in this paper:

1. *Seasonal tropical cyclone prediction*: The first task is to forecast the seasonal tropical cyclone (TC) count in some spatial regions including North Atlantic, North Pacific, and Northern Indian. TC includes hurricanes, tropical storms, typhoons, and cyclones.
2. *Seasonal hurricane prediction*: The second task is to forecast the seasonal hurricane count, with emphasis on landfall hurricanes. Hurricanes consists of the landfall hurricanes and the offshore hurricanes. Hurricanes lead to major natural disasters in the regions of landfall.
3. *North Africa rainfall prediction*: The third task is to forecast the seasonal rainfall in North Africa, especially, in the Sahel area, which is highly related to meningitis epidemics that affects more than 200,000 people throughout the African Sahel region annually.

We model each of these extreme event forecasting tasks as a forecast oriented, multi-class classification problem.

Formally, assume that the *multi-phase* system during the extreme event $e = (C, T_f, L_e)$ can be characterized by one of its phases, $C \in \{C_1, C_2, \ldots, C_s\}$ at some future time period T_f and in some event's spatial location region L_e. Can the algorithm A predict C given the spatio-temporal multivariate feature set F over space $L \supseteq L_e$ and time $T = (T_f - \Delta T, T_f)$? Note that the temporal resolution, ΔT, is domain-specific (e.g., 1–5 months for hurricanes). For the sake of simplicity, we assume that the number s of distinct system's phases/states is finite. For example, the seasonal hurricane activity can be broadly categorized as "above normal" (say, more than six hurricanes in a season), "normal," or "below normal" (say, less than four hurricanes in a season) during hurricane season $T_f = \{\text{July-November}\}$ in region $L_e = \{\text{North America}\}$ [Chu *et al.*, 2007]. We call this problem a ***forecast-oriented classification of spatio-temporal extreme events*** or FORECAST for short.

The intent of our problem is not to predict an actual numerical magnitude of the response, instead to seek proper classification into unambiguous groupings that provide enough information to make proper decisions, as many regression models are ultimately being translated into such coarser scales [Chu *et al.*, 2007] for impact assessment. Thus, in this paper, all observed extreme event count series are classified into three classes with a distribution of 40% as "normal" and 30% each as "below normal" and "above normal."

The FORECAST problem is different from traditional classification machine learning problem, since FORECAST aims to forecast the *future* phase of the system given its characteristics *prior* to the time-frame of interest unlike existing classification problem that predicts what phase the system *currently* belongs to, given its *current* characteristics.

3 Data Construction and Challenges

3.1 Data

We construct seasonal tropical cyclone (TC) count series from 1950 to 2011 of three main regions of Northern Hemisphere: North Atlantic, North Pacific, and Northern Indian. These series are obtained from Atlantic hurricane database (HURDAT) at the National Climatic Data Center, Central Weather Bureau [Chu *et al.*, 2007], and JTWC Northern Indian Ocean best track data. These datasets include hurricanes, tropical storms, typhoons, and cyclones that occurred from July through November in the North Atlantic basin, North Pacific basin, and Bengal and Arabian Sea basins. The landfall hurricanes that strike land are distinguished by using the "Hit" feature of the HURDAT. Likewise, hurricanes that made landfall in Mexico are also considered as landfall hurricanes in our analysis. Sahel rainfall indices from 1951–2004 are obtained by averaging seasonal (July through September) mean Precipitation data over (10-20°N, 20W–20°E). And monthly Precipitation data is obtained from the Climate Research Unit at a $0.5^\circ \times 0.5^\circ$ latitude and longitude resolution for the 1951–2004 period.

The global monthly mean sea level pressure (SLP), precipitable water (PW), sea surface temperature (SST), tropospheric vertical wind shear (VWS), relative humidity (RH) and wind speed (WSPD) data from preceding January through June are used as predictors to forecast the North Atlantic, North Pacific, and Northern Indian TC and Sahel rainfall classes. SLP, PW, RH, and WSPD are NCEP/NCAR reanalysis datasets. They are available at a $2.5^\circ \times 2.5^\circ$ latitude and longitude resolution. SST is from the NOAA Climate Diagnostic Center in Boulder, Colorado, at a resolution of $2^\circ \times 2^\circ$ latitude and longitude. VWS is calculated by computing the square root of the sum of the square of the difference in zonal wind component between 850 and 200 hPa levels and the square of the difference in meridional wind component between 850 and 200 hPa levels from NCEP/NCAR reanalysis data. The six variables combined could contribute a total of 411,480 features. All datasets are available at CUCIS Center[1] of Northwestern University.

3.2 Mathematical Abstraction

In traditional supervised classification, a model is learned from a matrix representation of the original data with m rows corresponding to a set E of observations, or events, and n columns corresponding to a set F of features that characterize each event. In addition, a column vector associates each event with its class from a finite set C of available classes. Once learned, the model predicts what class the target event defined over the same features F belongs to.

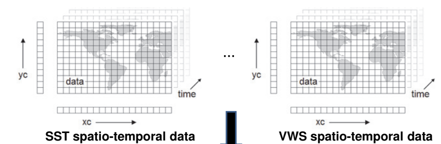
Both the forecasting nature of our problem and the multivariate spatio-temporal nature of the data necessitate a *mathematical abstraction* that could transform this data into a mathematical form suitable for a machine learning task, in general, and *forecast oriented classification*, in particular.

Formally, let V be a set of variables (such as SST, SLP, and VWS) that characterize the system over spatial locations L, defined over spatial (latitude, longitude, altitude) grid points, and over time period T (e.g., 1950-2011). And suppose that each extreme event e can be classified based on some event-specific classification taxonomy, C. In the context of the target extreme events, such as hurricanes or droughts, let us also assume that $T = T_1 \bigcup T_2 \bigcup \ldots \bigcup T_m$, where $T_i \bigcap T_j = \emptyset$ and $i \neq j$, is divided into m *coarse-grain* time intervals (e.g. m calendar years) during which an extreme event e can oc-

[1] http://cucis.ece.northwestern.edu/projects/Expeditions/

cur over some spatial region $L_e \subseteq L$ with some probability. Let us further assume that each time interval $T_j \in T$ is partitioned into the *fine-* or *coarse-grain observable* $T_{j,o}$ time period and the *coarse-grain forecastable* $T_{j,f}$ time period ($T_j = T_{j,o} \bigcup T_{j,f}$ and $T_{j,o} = T_{i,o}, T_{j,f} = T_{i,f}, \forall i, j \in \{1, 2, ..., m\}$).

Fig. 1 illustrates a mathematical abstraction using SST and VWS as variables, or predictands, defined over $T = (1950 - 1952)$ during the months of $T_{*,o} = \{\text{May, June}\}$ over (latitude, longitude) spatial grid points for the sea-level altitude. The class label is inferred based on the historical record of observed hurricanes in North America during $T_{*,f} =$ (July-November) hurricane season.



Year	SST _ 0°N_ 0°E_May	SST _ 0°N_ 0°E_June	SST _ 2°N_ 0°E_June	...	VWS _ 0°N_ 0°E_May	...	Class
1950	3	4	2	...	6	...	Above
1951	3	3	4	...	7	...	Above
1952	2	4	5	...	10	...	Normal

Time T — Features, F: Variable_Latitude_Longitude_Time — Class C

Figure 1: A mathematical form for forecast oriented classification of hurricane events.

3.3 Challenges

Traditional machine learning methods would face a number of technical challenges due to the characteristics of multivariate, spatio-temporal data, "the curse of dimensionality", and inter-correlated features.

- *Multivariate, spatio-temporal nature*: The data in real world dynamic systems are often with multiple or even tens of spatio-temporal variables (e.g., SST, SPL, VWS etc.), which requires a methodology that could naturally support multi-variate *spatio-temporal* data, which, to the best of our knowledge, no existing classification methodologies are particularly designed for.
- *The curse of dimensionality*: Another difficulty is how to deal with the enormous number of features that could easily reach thousands or even hundreds of thousands. Such enormous feature space could easily lead to the problem, coined by Bellman as "the curse of dimensionality" [Bellman, 1961].
- *Inter-correlated and non-linear relationships*: It is often the case that a coordinated, not independent, action of several features determines what phase a given system is in. Complex dynamic systems often operate in multiple phases, described as having similar defining characteristics but whose feedbacks behave in nonlinear fashion. Such non-linear cooperative or competing interactions between the features often form hierarchical functional modules (e.g., communities) that act not only on different spatial and temporal scales but also in response to fluctuations induced by endogenous and exogenous factors.

3.4 Performance Evaluation Metrics

Several metrics can be used to evaluate FORECAST's performances: accuracy, Heidke Skill Score, Peirce Skill Score, and Gerrity Skill Score [Jolliffe and Stephenson, 2003]. Accuracy is defined as the ratio of the number of correctly classified data points to the total number of data points in the test set.

Some preliminary results of the three real-world extreme event prediction tasks can be found in our work [Chen *et al.*, 2011; 2012; 2013].

4 Conclusion

In this paper, the spatio-temporal extreme event prediction problem has been modeled as a new supervised machine learning problem. We have constructed predictor and predictand data sets for three real-world extreme event prediction tasks including seasonal extreme event forecasts of Northern Hemisphere tropical cyclone counts, North Atlantic landfalling hurricane counts, and Sahel rainfall intensity. Many interesting directions to explore the multivariate spatio-temporal extreme event data include designing new feature selection technologies, building new ensemble of classifiers, mining spatio-temporal relationships, etc.

Acknowledgments

This work is supported in part by NSF awards CCF-0833131, CNS-0830927, IIS-0905205, CCF-0938000, CCF-1029166, and OCI-1144061; DOE awards DE-FG02-08ER25848, DE-SC0001283, DE-SC0005309, DESC0005340, and DESC0007456; AFOSR award FA9550-12-1-0458.

References

[Bellman, 1961] R. E. Bellman. *Adaptive control processes: a guided tour*. A Rand Corporation Research Study Series. Princeton University Press, 1961.

[Chen *et al.*, 2011] Z. Chen, T. Pansombut, and *et al.* Forecaster: Forecast oriented feature elimination-based classification of adverse spatio-temporal extremes. *NCSU Technical Report:1840.2/2408*, 2011.

[Chen *et al.*, 2012] Z. Chen, W. Hendrix, and *et al.* Discovery of extreme events-related communities in contrasting groups of physical system networks. *Data Mining and Knowledge Discovery*, 2012.

[Chen *et al.*, 2013] Z. Chen, J. Jenkins, and *et al.* Automatic detection and correction of multi-class classification errors using system whole-part relationships. *SDM*, 2013.

[Chu *et al.*, 2007] P. S. Chu, X. Zhao, and *et al.* Climate prediction of tropical cyclone activity in the vicinity of Taiwan using the multivariate least absolute deviation regression method. *Terr. Atmos. Ocean. Sci.*, 18(4):805–825, October 2007.

[Jolliffe and Stephenson, 2003] I. T. Jolliffe and D. B. Stephenson. *Forecast Verification: A Practitioner's Guide in Atmospheric Science*. Wiley and Sons, 2003.

[Molesworth *et al.*, 2003] A. M. Molesworth, L. E. Cuevas, and *et al.* Environmental risk and meningitis epidemics in Africa. *EID*, 9(10):1287–1293, 2003.

[Schiermeier, 2010] Q. Schiermeier. The real holes in climate science. *Nature*, 463:284–287, 2010.