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Autoencoder-driven weather clustering for source estimation during nuclear events

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A B S T R A C T

Emergency response applications for nuclear or radiological events can be significantly improved via deep feature learning due its ability to capture the inherent complexity of the data involved. In this paper we present a novel methodology for rapid source estimation during radiological releases based on deep feature extraction and weather clustering. Atmospheric dispersions are then calculated based on identified predominant weather patterns and are matched against simulated incidents indicated by radiation readings on the ground. We evaluate the accuracy of our methods over multiple years of weather reanalysis data in the European region. We juxtapose these results with deep classification convolution networks and discuss advantages and disadvantages. We find that deep autoencoder configurations can lead to accurate-enough origin estimation to complement existing systems, while allowing for rapid initial response.

1. Introduction

In the field of atmospheric dispersion modelling and its applications for supporting decision making during events of atmospheric releases of hazardous substances (*e.g.* radioactive material), *inverse source-term estimation* and *source inversion* refer to computational methods aiming at estimating the location and/or the emitted quantities of the hazardous material using both observations (readings on the ground) and results of dispersion models. Such methods are typically used when the presence of a hazardous substance above the background levels in the air is detected by an existing monitoring network, while its origin is unknown.

The most characteristic example of a real case involving radioactive elements that have been detected before the release was officially announced is the Chernobyl Nuclear Power Plant accident[1]. The Acerinox (or Algeciras) incident is another example of an unknown radioactive release that was traced back after radioactivity levels higher than the background had been observed at very long distances from the release location (Noureddine et al., 2003).

Depending on various factors, such as the spatial resolution desired, traditional inverse modelling can be computationally expensive, and therefore time-consuming, rendering its application problematic when timing is critical. In addition, atmospheric dispersion models, *e.g.* HYSPLIT (Draxler, 1999; Stein et al., 2015), are complex pieces of software that require expert training and case-by-case application. In this paper we present a novel, complementary approach based on data analytics and deep learning. Our goals are to effectively transfer the computational bulk before the time of such an event taking place, create reusable data by-products of value and complement existing emergency response methodologies. While the computational bulk, involving the training of deep feature learning models, is inherently time-consuming, it leads to rapid (in the order of a few seconds) initial estimates during events through the reusability of the data and models generated.

Focusing on the European region, we cluster re-analysis weather data in order to derive weather circulation patterns, which affect plume dispersion. We then calculate plume dispersions for a

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[1] http://www.irsn.fr/EN/publications/thematic-safety/chernobyl/.

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number of European nuclear power plant facilities of interest, based on representative cluster descriptors. Last, we match previously unseen weather to the weather patterns we have learned and rank the nuclear facilities according to how well their plume dispersion for the closest weather patterns match current hypothetical radiation measurements.

This work combines data analytical and machine learning methods and large weather and atmospheric dispersion datasets and models in a single framework for rapid source estimation.

We make the following contributions:

1. we propose and evaluate a novel data-driven methodology for release origin estimation;
2. we evaluate a series of autoencoder configurations, followed by *k*-means clustering applied on weather re-analysis data;
3. we juxtapose our method with deep convolution networks for classification, discussing their respective advantages and disadvantages; and
4. we present an application prototype for the rapid estimation of release origin and its implementation.

In the following section we provide a succinct discussion of related approaches, technologies and methods. In Section 3 we present the proposed methodology and rationale, while in Section 4 we provide a discussion of our evaluation methodology and discuss results and findings. In Section 5 we present a pilot application showcasing the proposed approach. In Section 6 we conclude the paper and discuss directions for future work, while in Section 7 we point to software resources to encourage cross-examination and replication.

2. Related work

This study combines algorithms and methods borrowed from a number of disciplines, such as machine learning, weather circulation clustering, atmospheric dispersion and weather modelling. An overview of relevant work is provided below.

2.1. Discovering weather patterns

Over the last decades there have been several studies attempting to automatically discover weather patterns via unsupervised hierarchical and iterative clustering (Huth et al., 2008), as part of synoptic climatology (Yarnal et al., 2001). Many of these studies have attempted to establish statistically robust representations based on the calculation of principal components in, what this body of literature refers to as, S- and T-modes. S-mode refers to the typical application of principal component analysis (PCA) per weather sample used for feature reduction, while T-mode refers to the application of PCA per grid point or feature (In our evaluation, in Section 4, we refer to the T-mode also as PCA^T, to indicate cases where PCA has been applied on the “transposed” form of the data samples.). Indicatively, Huth (1996) summarises and compares correlation, sums-of-squares, agglomerative hierarchical, PCA, *k*-means and hierarchical agglomerative clustering algorithms. These algorithms were executed on geopotential height (GHT) at a pressure level of 700*hPa* and were evaluated using internal metrics, such as consistency and robustness. According to Huth, there is no clear winner for clustering weather patterns, however T-mode PCA appears to produce clusters that resemble manually identified weather patterns more accurately. Methods based on more recent advances in neural networks, employing self-organising maps, have also been reported (Cavazos, 2000; Hewitson and Crane, 2002).

Other classification and clustering approaches tailored to specific applications or geographical regions have been published. Teixeira de Lima and Stephany (Teixeira de Lima and. Stephany, 2013) evaluate a multitude of weather variables for extreme weather classification. Straus et al. (Straus et al., 2007). use a modified version of *k*-means clustering for the pressure level of 200*hPa* and zonal winds to discover and analyse winter circulation regimes over the Pacific-North American region. Hsu and Cheng (2016) evaluate daily average surface wind measurements to discover weather patterns affecting air pollution in western Taiwan. Focusing on the urban heat island, the phenomenon in which an urban area is significantly warmer than its surrounding rural areas due to human activity, Hoffmann and Schlünzen (Hoffmann and Heinke Schlünzen, 2013) study *k*-means on a number of variables such as GHT, relative humidity, vorticity, and others. Bannayan et al. use temperature, precipitation and solar radiation in a k-nearest neighbour approach for real-time prediction of daily weather data (Bannayan and Hoogenboom, 2008). Extracting information out of weather patterns has also been reported in cases of fire spread modelling by Duane et al. (Duane et al., 2016). Al-Alawi et al. employ PCA for feature reduction, as part of a combination of principal component regression and feed-forward neural networks, for the prediction of ozone concentration (Al-Alawi et al., 2008).

Far from being exhaustive, the above studies are indicative of the multitude of applications, clustering and classification approaches reported in the wider area of environmental modelling. While part of our study involves discovering useful weather patterns, our application of these clusters is specific to capturing the conditions leading to similar plume dispersions. Our experiments, reported in Section 4, focus on GHT as a feature predictive of circulation patterns and consequently, plume dispersion.

2.2. Autoencoders for feature reduction

An autoencoder (LeCun et al., 1998a; Bengio, 2009; Goodfellow et al., 2016) is an unsupervised feed-forward neural network designed to approximate the identity function, *i.e.* one that attempts to learn a function $h(x) = \hat{x} \approx x$, where x and $\hat{x}$ denote the input and output vectors respectively. Post-training, applications typically disregard the output of autoencoders, instead making use of the activation values of the hidden layers. These constitute latent representations of the input. The activations of simple, single-layer auto-encoders have been shown to be equivalent to principal components (Bourlard and Kamp, 1988).

In its simplest form, when there is a single hidden layer and the number of hidden units equals the number of inputs, the autoencoder is too successful in replicating the input, leading to overfitting. Various methods have been suggested to avoid overfitting, *e.g.* having fewer hidden than input units, enforcing activation sparsity or introducing noise which the auto-encoder learns to compensate for (Vincent et al., 2008; Vincent and Larochelle, 2010). An alternative approach is to use deeper configurations of stacked autoencoders, where inner layers encode and decode previously encoded vectors. Encodings generated by stacked autoencoders can capture deeper statistical representations of the input data.

Autoencoders have been augmented by different types of deep neural networks, such as convolutional networks, or *convnets*. Convnets (LeCun et al., 1998b; Goodfellow et al., 2016) are designed to discover multi-dimensional patterns of varying sizes and have been used, stand-alone or as part of more complex configurations, primarily in classification-based image recognition. Convolutional autoencoders are formed by stacking convolutional layers, fully connected layers and de-convolutional layers in a single configuration in order to capture feature hierarchies in the input space (Masci et al., 2011).

In this study we evaluate simple, stacked and convolutional