Modelling and Classifying Random Phenomena

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26 January, 2010

Overview

- The Comprehensive Test Ban Treaty
- Motivation
- The atmosphere and the major dispersion processes
- Modelling atmospheric dispersion
- The simulation process
- Preliminary results

The Comprehensive Test Ban Treaty (CTBT)

The CTBT is a United Nations treaty which will **bans all nuclear explosions in the environment** when it enters into force.
http://www.ctbto.org/

CTBT - Problem Statement

Develop and deploy a verification regime capable of ensuring the integrity of the CTBT by the time it enters into force.

Choices inherent in the development of a verification strategy.

1. Feature selection
2. Procedure for the collection and/or measurement of features
3. Receptor placement
4. Classification strategy

CTBT - Design decisions

(1) Feature selection: ${}^{131m}Xe, {}^{133}Xe, {}^{133m}Xe$ and ${}^{135}Xe$
  - selected for intermediate rates of decay
  - due to their property of being inert

(2) Air sampling equipment
  - sampling occurs over 12 or 24 hours
  - filter is cooled
  - followed by analysis which produces a gamma ray spectrum
  - feature vector extraction

CTBT - Design decisions

(3) Receptor location is largely an open question
  - ideally, elevated and subject to regular wind
  - the form of the global network which maximizes the likelihood of detection is not entirely clear

(4) Classification
  - input feature vector
  - output detonation decision
  - complicating factors: radioxenon emitted from medical isotope production facilities and nuclear power generation

Motivation

- Health Canada Dataset
  - real (background) data collected from five receptor sites
  - infused with artificial explosion data
- Limitations
  - explosion instances greatly outnumber background instances
  - overall limited supply

Related Work

- Data generation is particularly useful when:
  - Limited or, no, "real" data available for one or more classes
  - Added flexibility to increase understanding of classifier and improve confidence in future performance
- Both motivating factors in terms of CTBT verification.
  - limited/no "real" explosion data
  - HC background data under-represented - particularly a concern for one-class learning
  - Developed classifiers will be deployed in a highly variable environment
    - Manipulations to the generation process will provide insight into classifier behaviour during evolving conditions. - ex. MIs come on- or go off-line, change in global wind patterns etc. -
- see [Dietterich97, Alaiz08, Langley94, Zhu04]

Atmospheric Processes

- Fate of pollutants affected by atmospheric flows
  - byproduct of energy exchange
  - interplay between lower atmosphere and the earth's surface

Modelling the Atmosphere

- divided into sections based on vertical temperature gradient
- pollutants generally emitted into the troposphere
    - lowest layer
    - rises approx. 15km
    - contains atmospheric boundary layer (ABL) and convective boundary layer (CBL)

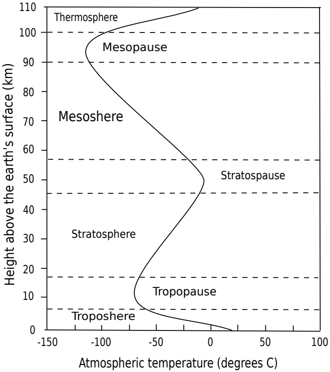


Figure: Vertical temperature profile of the atmosphere (recreated from [Cooper03].)

Atmospheric Processes

- Atmospheric boundary layer
  - lowest portion of the troposphere
  - motion suffers from frictional drag
  - resulting energy exchange affects a temperature and moisture profile
  - produces convective eddies in the above CBL
- Convective boundary layer
  - bounded below by ABL and on top by inversion layer
  - upper bound is dependent upon meteorological conditions and has a significant effect on surface pollution levels

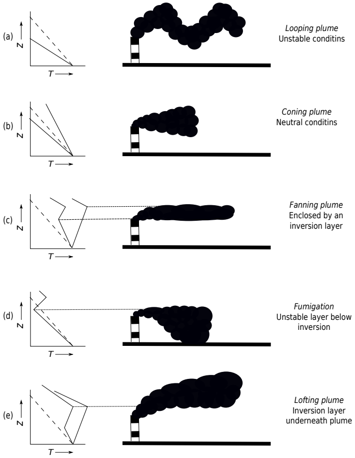
Atmospheric Processes

- Dispersion processes
  - advection: transfers pollution in the direction of mean wind
  - diffusion: shifts concentration levels down the gradient scale

  - Advection
    - limited by frictional forces resulting from surface roughness
    - wind speed increases significantly in first 10 metres
    - surface effect dissipates beyond 1 kilometre
  - Diffusion
    - random process, causes eddies to exchange and mix with neighbouring parts of atmosphere
    - largely dependent upon surface roughness and buoyancy.
    - stability term can be used to classify the degree to which mixing occurs
    - stable: little mixing
    - unstable: well mixed

Atmospheric Processes

- Effect of mixing and layering on plume [Beychok94]
    - in the inset z vs T diagram, the dashed line represents dry adiabatic lapse rate and the solid line represents measured lapse rate.
    - out is the resulting plume



Modelling the Atmosphere

Frames of reference

- Eulerian:
  - views atmosphere from a fixed point
  - inspects parcels of air as they move past
- Lagrangian:
  - describes behaviour wrt moving fluids
  - point of reference within an advecting parcel

Modelling the Atmosphere

Lagrangian particle models

- mathematically follow pollutants as they disperse by:
    - applying calculations of the statistical trajectory of parcels
    - random walk approach
- previously used to model radionuclide dispersion by [Izraehl90, Desiato92]

Modelling the Atmosphere

K-theory

- adheres to the hypothesis of gradient transfers
    - ie. assumes a shift down the gradient scale
- provides a comprehensive description of atmospheric dispersion
- example of its application can be seen in [Lauritzen99, Maccracken78]

Modelling the Atmosphere

The main equation of K-theory:

$$\frac{D\overline{\chi}}{Dt} = \frac{\partial}{\partial x}\left(K_x \frac{\partial\overline{\chi}}{\partial x}\right) + \frac{\partial}{\partial y}\left(K_y \frac{\partial\overline{\chi}}{\partial y}\right) + \frac{\partial}{\partial z}\left(K_z \frac{\partial\overline{\chi}}{\partial z}\right) \qquad (1)$$

where:

t:	time
$\overline{\chi}$:	the mean concentration of the pollutants
$K_{x,y,z}$:	eddie diffusivity in the three coordinate directions
$\frac{D\overline{\chi}}{Dt}$:	the Lagrangian time derivative

accounts for diffusion in the three component directions (anisotropic)

Modelling the Atmosphere

Assume isotropic diffusion:

- this assumes diffusion is constant and independent of spacial direction
- resulting eq'n is analogous to Fick's law of molecular diffusion

$$\frac{D\overline{\chi}}{Dt} = K\nabla^2 x \tag{2}$$

where:

$$\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}$$

and

$$K = K_x = K_y = K_z$$

- this can be used to model diffusion in 1-, 2- or 3-dimensions

Modelling the Atmosphere

1-dimensional Fickian diffusion eq'n:

$$\frac{\partial \overline{\chi}}{\partial t} + \overline{u}\frac{\partial \overline{\chi}}{\partial x} = K\frac{\partial^2 \overline{\chi}}{\partial x^2} \tag{3}$$

where:

$$\overline{v} = \overline{w} = 0$$

and

- the first term represents the rate of change of $\overline{\chi}$ at a selected fixed point in space
- the second term represents the advection of the pollutant at velocity $\overline{u}$

Modelling the Atmosphere

Gaussian puff model:

- sol'n to Fickian diffusion equation
- models diffusion from an instaneous point source of emission strength Q
- assume mean concentration of dispersing pollutant is forms a Gaussian distribution

$$\overline{\chi}(x, y, z, t) = \frac{Q}{(4\pi t)^{\frac{3}{2}}(K_x K_y K_z)^{\frac{1}{2}}} exp\left[-\left(\frac{(x-\overline{u}t)^2}{4K_x t} + \frac{y^2}{4K_y t} + \frac{z^2}{4K_z t}\right)\right]$$

Modelling the Atmosphere

Boundary conditions Gaussian puff model:

1. $\overline{\chi} \rightarrow 0$ *as* $t \rightarrow \infty$ for all coordinates $-\infty < x, y, z < \infty$
2. $\overline{\chi} \rightarrow 0$ *as* $t \rightarrow 0$ for all coordinates except where $x, y, z = 0$
3. $\int_{-\infty}^{\infty} \overline{\chi} dxdydz = Q$

- [Oliveira98] applied a variant of the puff model to predict the dispersion of radionuclides from a nuclear power plant in Brazil

Modelling the Atmosphere

Gaussian plume model:

- models diffusion from a continuous point source (Q), emitted from an elevated industrial stack
- infinite number of puffs superimposed on each other
- mathematically speaking, integrate with respect to time
- as a matter of convenience, diffusion along x-axis is ignored

$$\chi(x, y, z, t) = \frac{Q}{2\pi\sigma_y\sigma_z\overline{u}} exp\left(-\left(\frac{y^2}{2\sigma_y^2} + \frac{z^2}{2\sigma_z^2}\right)\right)$$

Modelling the Atmosphere

Gaussian plume model:

- account for reflection at surface

$$\chi(x,y,z,t) = \frac{Q}{2\pi\sigma_y\sigma_z\overline{u}} exp\left(-\frac{y^2}{2\sigma_y^2}\right) \left[exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right) + exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right]$$

where:

h is the height of the plumes centreline

- in much the same way, reflection at an inversion layer can be accounted for
- for some further examples of the application of Gaussian models see [AlKhayat92, Simmonds93, Lyons90]

Simulating Dispersion

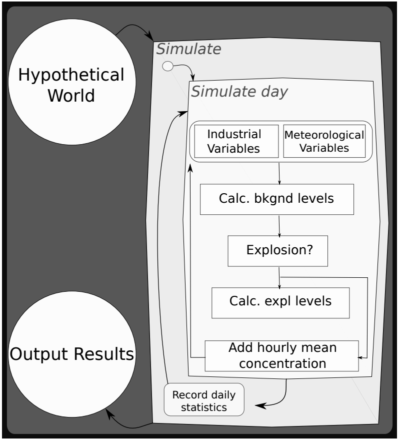
Objective:

- Generate a dataset containing a series of radioxenon measurements
- Receptor-specific datasets contain feature vectors of:
  - cumulative quantity of radioxenon measured over 12 or 24 hours
  - class label (background or explosion)

Simulating Dispersion

1. Define hypothetical world
2. Simulation for j=1:n days
    (i) For each day, simulate i=1:24 hours
        - generate Gaussian random variables about the means
        - calculate background radioxenon levels
        - if explosion, added expls levels to bkgnd levels
        - add hourly mean to cumulative daily count

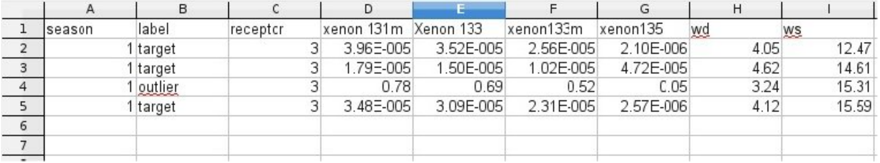
    (ii) Record daily value
3. Output dataset



Simulating Dispersion

Sample dataset:

- Important features are xenon 131m, 133, 133m and 135
- Considerations season, wind speed and direction

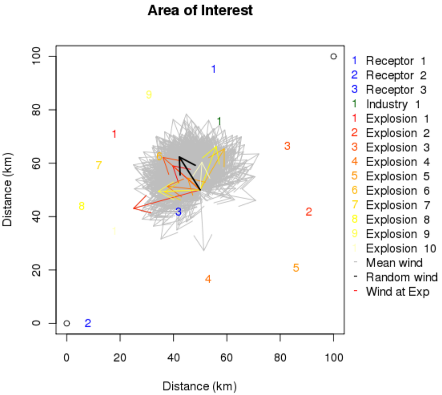


	A	B	C	D	E	F	G	H	I
1	season	label	receptor	xenon 131m	Xenon 133	xenon133m	xenon135	wd	ws
2	1	target	3	3.96E-005	3.52E-005	2.56E-005	2.10E-006	4.05	12.47
3	1	target	3	1.79E-005	1.50E-005	1.02E-005	4.72E-005	4.62	14.61
4	1	outlier	3	0.78	0.69	0.52	0.05	3.24	15.31
5	1	target	3	3.48E-005	3.09E-005	2.31E-005	2.57E-006	4.12	15.59
6									
7									

Simulating Dispersion

Sample map:

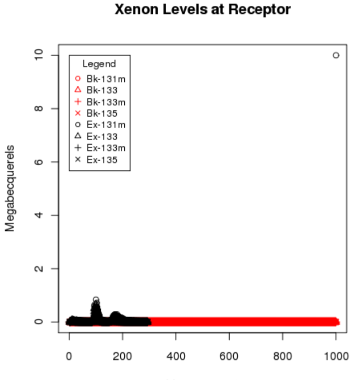
- 1 industrial emitter (green)
- 3 receptors (blue)
- 10 explosions (heat colours)



Simulating Dispersion

plotted results for receptor 2:

- background data in red
- explosions in black
- generally up-wind from industry → low background levels
- two peaks (expl 4 and expl 5)



Preliminary Results

Classifier	**Class**	**TPR**	**FPR**	**AUC**
MLP	target	0.845	0	0.896
	outlier	1	0.155	0.896
J48	target	0.997	0	0.990
	outlier	1	0.003	0.990
IBK	target	0.995	0	0.998
	outlier	1	0.005	0.998
NB	target	0.039	0.1	0.754
	outlier	0.990	0.964	0.754
CDCPE [Hempstalk08]	target	0.902	0.013	0.650
	outlier	0.087	0.098	0.650

Conclusion

- Examined strategies for modelling atmospheric dispersion
- In the spirit of the CTBT
    - applied a Gaussian assumption to model the dispersion of radioxenon
    - generate background noise and random Phenomena
- Utilized Weka to classify the preliminary dataset

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