Uncertain weather, uncertain climate

The slippery slope into Bayesian statistics

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University of Toronto, March 2013
Outline

- Inverse problems in 19th century
- Weather observations
- How to make a forecast
- Past climate: what we measure
- Reconstructing past climate

Big ideas

Divide up the problem into two parts:

- What do know about the state of the atmosphere?
- How is an observation related to what you know?

- prior information, likelihood of observing data,
  → posterior probabilities
"Good-morning, madam," said Holmes cheerily. "My name is Sherlock Holmes."
Her features and figure were those of a woman of thirty, but her hair was shot with premature grey, and her expression was weary and haggard.
"We shall soon set matters right, I have no doubt. You have come in by train this morning, I see. ... and yet you had a good drive in a dog-cart, along heavy roads, before you reached the station. " 
"The left arm of your jacket is spattered with mud in no less than seven places. The marks are perfectly fresh.

There is no vehicle save a dog-cart which throws up mud in that way, and then only when you sit on the left-hand side of the driver."
Holmes’ calculation

Before meeting Ms. Helen Stoner:

- A PRIOR probability of type of vehicle

Knowledge of vehicles effects:

- LIKELIHOOD of observation given type of vehicle

Combine prior with observation:

- POSTERIOR is a product: Likelihood of mud stains given type of vehicle \times Probability of type of vehicle

Maximize over vehicle
Holmes’ conclusion – the highest probability

- vehicle = dog cart
Some differences

Holmes’ genius:
Uses observations without assuming much prior information!

Weather and climate applications:

- Our observations are not as decisive – we must rely more on the prior information.

- Have to use a computer to do the computation!

NCAR/U Wyoming, Yellowstone Supercomputer, 70,000+ processors.
Making a weather forecast

Credits: Data Assimilation Research Section, NCAR
Jeff Anderson, Tim Hoar, Kevin Raeder

The ensemble Kalman filter
Describing the atmosphere

- divide up the atmosphere into a large 3-d grid $\approx 144 \times 96 \times 27 = 1/3$ million points
- the temperature, pressure, water vapor and the wind for each grid box for each time – need at least 6 variables to describe state.

the state vector at one time:

atmosphere $= \text{about 2 million numbers}$

Even this is only about 200km resolution.
Prior information for the atmosphere

The atmospheric state is uncertain.

Represent the uncertainty with a sample (ensemble) of states – all equally plausible and each physically consistent.

\[ \text{atmosphere}^1, \text{atmosphere}^2, \text{atmosphere}^3, \ldots \]

For this example there will be 80 members in the ensemble.
An example

Height where the pressure is 500hP, FEB 17, 2003 (12Z)

- 80 member ensemble
- Just a small, 2-d glimpse – the PRIOR is global and 3-d.
Observations for the atmosphere

Surface observations

rawinsondes (balloons)

satellite images

remotely sensed

... ???
LIKELIHOOD: the probability of an observation given a state of the atmosphere

- All observations have some degree of measurement error.
- All can be related back to the state of the atmosphere.
12Z FEB 17, 2003, height at 500hP measured at 5530 (m)
POSTERIOR is a product:

Likelihood of observation given atmosphere
$\times$ Probability of atmosphere

Difficult to compute exactly . . .

Use the ensemble
The algorithm

Updating the estimate at the Peterborough grid point. Actual observation at 5530 (m). Prior prediction is 5551 (m)

- Combining observation and PRIOR prediction gives POSTERIOR estimate of 5545 (m).

- Have the PRIOR distribution for the observation and at the grid point. *Fit a line by least squares.*

- Use scatterplot relationship to get POSTERIOR estimate for Peterborough grid box of 5573 (m).
Updating the ensemble

- Shrink the ensemble members to the POSTERIOR estimate

500hP height at observation location

5520  5540  5560  5580

height at WMW

- Use scatterplot relationship to get POSTERIOR values of ensemble members at Peterborough grid box.
The full POSTERIOR ensemble

Repeat this algorithm for all available observations at this time and for every value in the state.

This is why we need a supercomputer!
Making a forecast

Use a weather model, $M$, to advance the current state into the future – this is the forecast.

atmosphere 6 hours later = $M(\text{atmosphere})$

A state-of-the-art $M$:

• based on detailed physics of the atmosphere

• millions of lines of code, requires a supercomputer

Apply $M$ to the POSTERIOR ensemble members

atmosphere 6 hours later$_1$ = $M(\text{atmosphere}_1)$
atmosphere 6 hours later$_2$ = $M(\text{atmosphere}_2)$
\[ \ldots \]
atmosphere 6 hours later$_{80}$ = $M(\text{atmosphere}_{80})$
The 6 hour forecast

PRIOR ensemble at 12Z

POSTERIOR ensemble advanced 6 hours
The forecast becomes the new PRIOR …
Estimating past climate

Credits: Martin Tingley and Peter Huybers, Harvard U

Bayesian Hierarchical Models
How do we know temperatures before thermometers?

Surface temperatures are related to other observations:
- e.g. tree ring width and density, pollen, ice cores and lake sediments.
The Mann et al reconstruction

Northern Hemisphere temperatures 1000AD - 2000AD

Mann, Bradley and Hughes 1998 Nature.
Mann et al. (1999)

"... the 1990s are likely the warmest decade, and 1998 the warmest year, in at least a millennium"

- Used informally (by others) to argue human influence on climate
- The scientific process: the field has moved on from this initial work.
An ensemble of NH reconstructions

Circa June 2006:
Recent statistical work
Martin P. Tingley & Peter Huybers (2013)

Goal: Create a spatial estimate of annual temperatures for high Northern latitudes and for the past 600 years.
Prior information

State is annual \textit{temperature} on 96, 5\times5 degree grid boxes above 45N.

Use a statistical model to capture smoothness of the annual temperatures

\begin{itemize}
  \item over space
  \item from year to year.
\end{itemize}

\[
    \text{temperature}_{t+1} = M(\text{temperature}_t) + \text{random shocks}
\]

\begin{itemize}
  \item \(M\) is simple
  \item random component mimics the effects of weather
\end{itemize}
**LIKELIHOOD:** the probability of an *proxy observation given the local state of the temperature*

- Each observation has a linear relationship with local temperature plus random error.
POSTERIOR is a product:

Likelihood of proxy observation given temperature \times Probability of temperature

Find temperature histories that represent the POSTERIOR distribution

- No simple formulas – need to use Monte Carlo sampling
- Analysis based on 4000 sample histories
- Statistical parameters are estimated along with histories.
Average temperature for the high latitude region:

Snapshots of four years

D. Nychka Uncertain weather, uncertain climate
Thank you! 