Where do spatial statistics and geoinformatics meet?

Edzer Pebesma



Geodätischen Kolloquium der Leibniz Universität Hannover

Jan 29, 2013

Where do spatial statistics and geoinformatics meet?

My answer will be partial (and egocentric). It will address the question at three levels

- engineering level:
 - Spatial and spatio-temporal data analysis in the R project
- societal level:
 - Spatial statistics, reproducible research
- scientific level:
 - Meaningful spatial prediction and aggregation

- INTAMAP: interoperability and automated mapping (2006-2009)
- UncertWeb: the uncertainty-enabled model web (2010-2013)
- both focus on interoperability, the model web, uncertainty, and web services
- outcomes:
 - Uncert ML, a markup language for probability distributions
 - 🕨 greenland
 - , a visualisation client for proba emporal data
 - R packages WPS4R, spacetime

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K a model web?

Engineering level: 1.

R

Use R!

Roger S. Bivand • Edzer J. Pebesma Virgilio Gómez-Rubio

Applied Spatial Data Analysis with R

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r-sig-geo monthly email list traffic



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CRAN Task View: Handling and Analyzing Spatio-Temporal Data

Maintainer: Edzer PebesmaContact:edzer.pebesma at uni-muenster.deVersion:2013-01-28

This task view aims at presenting the useful R packages for the analysis of spatio-temporal data.

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Please let the maintainer know if something is inaccurate or missing.

Although one could argue that all data are spatio-temporal, as they must have been taken somewhere and at some point in time, in many cases the spatial locations or times of observation are not registered, and irrelevant to the purpose of the study. Here, we will address the cases where both location and time of observation are registered, and relevant for the analysis of the data. The <u>Spatial</u> and <u>TimeSeries</u> task views shed light on spatial, and temporal data handling and analysis, individually.

Representing data

• In long tables: In some cases, spatio-temporal data can be held in tables (data.frame objects), with longitude, latitude and time as three of the columns, or an identifier for a location or region and time as columns. For instance, data sets in package plm for linear panel models have repeated observations for observational units, where these units often refer to spatial areas (countries, states) by an index. This index (a name, or number) can be matched to the spatial coordinates (polygons) of the corresponding area, an example of this is given by <u>Pebesma (2012, Journal of Statistical Software</u>). As these data sets usually contain more than one attribute, to hold the data in a two-dimensional table a *long table* form is chosen, where each record contains the index of the observational unit, observation time, and all attributes.



Journal of Statistical Software

November 2012, Volume 51, Issue 7.

http://www.jstatsoft.org/

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spacetime: Spatio-Temporal Data in R

Edzer Pebesma University of Münster

Abstract

This document describes classes and methods designed to deal with different types of spatio-temporal data in R implemented in the R package spacetime, and provides examples for analyzing them. It builds upon the classes and methods for spatial data from package **sp**, and for time series data from package **xts**. The goal is to cover a number of useful representations for spatio-temporal sensor data, and results from predicting (spatial and/or temporal interpolation or smoothing), aggregating, or subsetting them, and to represent trajectories. The goals of this paper is to explore how spatio-temporal data can be sensibly represented in classes, and to find out which analysis and visualisation methods are useful and feasible. We discuss the time series convention of representing time intervals by their starting time only. This document is the main reference for the R package **spacetime**, and is available (in updated form) as a vignette in this package.

	Year	Impact Factor (IF)	Total Articles	Total Cites
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	2010	2.647	60	1039
	2009	2.32	42	714
	2008	1.033	43	423

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	2	J R STAT SOC B	1369-7412	12345	3.645	5.281	0.793	29	>10.0	0.02073	5.382
	3	STAT SCI	0883-4237	3054	3.035	4.205	0.259	27	>10.0	0.00886	3.659
	4	ANN STAT	0090-5364	11722	3.030	3.700	0.423	104	>10.0	0.04315	4.157
	5	ECONOMETRICA	0012-9682	19659	2.976	4.700	0.688	48	>10.0	0.04393	8.648
	6	STAT METHODS MED RES	0962-2802	1835	2.443	2.988	0.500	36	>10.0	0.00570	1.930
	7	STATA J	1536-867X	1250	2.222	3.063	0.147	34	6.4	0.00604	1.871
	8	BIOSTATISTICS	1465-4644	2225	2.145	3.162	0.519	54	7.3	0.01154	2.313
	9	J R STAT SOC A STAT	0964-1998	1685	2.110	2.275	0.327	49	>10.0	0.00631	1.685
	10	PHARM STAT	1539-1604	422	2.067	2.160	0.463	67	4.1	0.00254	1.056
	11	J AM STAT ASSOC	0162-1459	21348	1.992	3.310	0.240	121	>10.0	0.03691	3.115

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Edzer Pebesma Edit

Professor of geoinformatics, University of Muenster Ealt spatial statistics - geostatistics - interoperability - reproducible research - R Ealt Verified email at uni-muenster.de Ealt My profile is public Ealt Link Homepage Ealt

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Societal level: OSS and reproducible research

Eos, Vol. 93, No. 16, 17 April 2012

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FORUM

The R Software Environment in Reproducible Geoscientific Research

PAGE 163

Reproducibility is an important aspect of scientific research, because the credibility of science is at stake when research is not reproducible. Like science, the development of good, reliable scientific software is a social process. A mature and growing community relies on the R software environment for carrying out geoscientific research. Here we describe why people use R and how it helps in communicating and reproducing research.

R is a multiplatform open-source software environment [*R Development Core Team*, 2012] that implements S, a language designed for data analysis. It prorelieving developers of the burden of multiplatform support. Package verification mechanisms make CRAN a reliable and powerful resource for users and developers.

When writing R packages, one assumes that R works in a certain way and will continue doing so. When the working of R changes, there is a chance that this change will break a package, i.e., stop an extension package from working, especially when the package was using R syntax sloppily. Although R core uses the 3500 extension packages on CRAN to verify the impact of planned changes, improvements that break some packages are at times needed. In such a case, maintainers of packages affected are notified in a timely way so that they can take

Societal level: spatial statistics @Elsevier



Scientific level:

Meaningful Spatial Prediction and Aggregation

Christoph Stasch^{a,*}, Simon Scheider^a, Edzer Pebesma^{a,b}, Werner Kuhn^a

^aInstitute for Geoinformatics, University of Muenster, Weseler Strasse 253, 48153 Muenster, Germany ^b52 North Initiative for Geospatial Open Source Software GmbH, Martin-Luther-King-Weg 24, 48151 Muenster, Germany

B

Abstract

The appropriateness of spatial prediction methods such as Kriging, or aggregation methods such as summing observation values over an area, is currently judged by domain experts using their knowledge and expertise. In order to provide support from information systems for automatically discouraging or proposing prediction or aggregation methods for a dataset, expert knowledge needs to be formalized. This involves, in particular, knowledge about phenomena represented by data and models, as well as about underlying procedures. In this paper, we introduce a novel notion of *meaningfulness* of prediction and aggregation. To this end, we present a formal theory about spatio-temporal variable types, observation procedures, as well as interpolation and aggregation procedures relevant in Spatial Statistics. Meaningfulness is defined as correspondence between functions and data sets, the former representing *data generation procedures* such as observation and prediction. Comparison is based on *semantic reference systems*, which are types

How do point data look?

```
> library(gstat)
```

> data(meuse)

```
> meuse[1:5, c("x","y","zinc")]
```

x y zinc 1 181072 333611 1022 2 181025 333558 1141 3 181165 333537 640 4 181298 333484 257 5 181307 333330 269

```
> co2 = read.csv("co2_emission_powerplants.csv")
> co2[1.5 _ c(llow mitude" _ llotitude" _ llotitude" _ 0007")
```

```
> co2[1:5, c("longitude", "latitude", "carbon_2007")]
```

longitude latitude carbon_2007

	44 450050	F1 00040	07400000
1	14.453050	51.83248	27400000
2	6.575827	51.05470	24100000
3	6.668831	50.99228	30400000
4	6.615766	51.03780	22200000
5	6.313576	50.83805	22000000

similar, but can we do similar things with them

3

Interpolating heavy metal concentration in soil

```
following Burrough & McDonell, 1998:
```

```
> coordinates(meuse) = ~x+y
> v = variogram(log(zinc)~1, meuse)
> v.fit = fit.variogram(v, vgm(1, "Sph", 900, 1))
> data(meuse.grid)
> gridded(meuse.grid) = ~x+y
> m.kr = krige(log(zinc)~1, meuse, meuse.grid, v.fit)
```

[using ordinary kriging]

```
> spplot(m.kr["var1.pred"])
```



(a) (a) (a) (a) (a)

Interpolating power plant CO₂ emissions

```
> # load the country border of Germany:
> librarv(cshapes)
> cntr <- cshp(date=as.Date("2008-06-30"))</pre>
> germany <- cntr[cntr$CNTRY_NAME == "Germany",]
> # clean co2 data:
> co2 <- co2[co2$latitude != 0 & co2$carbon_2007 != 0,
+ c("latitude","longitude","carbon_2007")]
> # convert table to Spatial:
> coordinates(co2) = ~longitude+latitude
> proj4string(co2) = proj4string(germany)
> # create interpolation grid:
> grd = spsample(germany, 10000, "regular", offset = c(0,0))
> gridded(grd) = TRUE
> # interpolate, idw:
> co2 interpolated <- krige(carbon 2007~1, co2, grd)</pre>
[inverse distance weighted interpolation]
```

Interpolated CO₂ emissions in 2007 (tons)



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Which one is meaningful?

At an unobserved location, what does

- a predicted zinc concentration in top soil mean?
- **b** predicted coal power plant CO₂ emission mean?

what does unobserved location mean?

- a a location, with soil, with "similar" conditions?
- **b** a site with
 - a power plant with unknown emission, or
 - an arbitrary site with no power plant?

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When is summing meaningful?

- > with(as.data.frame(meuse), sum(zinc))
- [1] 72806
- > with(as.data.frame(co2), sum(carbon_2007))
- [1] 407225925

Which of these two sums is meaningful?



Types of Reference System Domains.

Reference Do-	Туре	Description	Example
main			
Domain of a	D_s	All possible locations	$([-90, 90] \times$
Spatial Refer-		that are defined in a	$[-180, 180]) \subset \mathbb{R}^2$
ence System		spatial reference sys-	defined in WGS84
		tem; we restrict D_s	
		to $D_s \subset \mathbb{R}^2$	
Domain of a	D_t	All possible times	POSIX time (sec-
Temporal Refer-		defined in a tempo-	onds from 1st
ence System		ral reference system	January 1970 UTC)
			with $D_t \subset \mathbb{Q}$
Domain of a	D_q	Set of all values that	$[0,10^6]~\subset~\mathbb{R}$ with
Quality Refer-		a quality might take	unit ppm as de-
ence System			fined in Unified Code
			for Units of Measure
			(UCUM)
Domain of a Dis-	D_d	Set of discrete ob-	Set of coal power
crete Entities		jects or events.	plants in Germany in
			2010
crete Entities	\mathcal{D}_d	jects or events.	plants in Germany in 2010

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	Variable type	Functional type	Example
	Spatial Point	$SPP = "D_d \Rightarrow D_s"$	Locations of longleaf
	Pattern		pines in 4 ha of a nat-
			ural forest in Thomas
			County, Georgia
	Marked Spatial	MSPP =	Locations of longleaf
	Point Pattern	$"D_d \Rightarrow (D_s \times D_q)"$	pines in 4 ha of a nat-
			ural forest in Thomas
			County, Georgia with
			diameters-at-breast-
			heights (DBH)
	Temporal Point	$TPP = "D_d \Rightarrow D_t"$	Occurrence of earth-
	Pattern		quakes in an american
			county
	Marked Tempo-	MTPP =	Occurrence of earth-
	ral Point Pattern	$"D_d \Rightarrow (D_t \times D_q)"$	quakes in an american
			county with magnitudes
	Spatio-temporal	STPP =	Occurrence of earth-
	Point Pattern	$"D_d \Rightarrow (D_t \times D_s)"$	quakes at particular
			locations <in <and<="" space="" td=""></in>
			time

Types of Point Pattern Variables in Spatial Statistics

Types of Geostatistical and Lattice Variables in Spatial Statistics

Variable type	Functional type	Example
Geostatistical	$GEOST = "D_s \Rightarrow D_t \Rightarrow D_q"$	PM_{10} concentrations
Variable		across Germany
Lattice Variable	$LAT = "^r D_s \Rightarrow D_t \Rightarrow D_q"$	Number of doctor-
		prescriptions per
		consultation in cantons
		of the Midi-Pyrenees

Trajectory Variable Type in Spatial Statistics

Variable type	Functional type	Example
Trajectory	TRAJECT =	paths of tracked an-
	$"D_d \Rightarrow D_t \Rightarrow D_s"$	imals
Marked Trajec-	MTRAJECT =	paths of tracked an-
tory	$"D_d \Rightarrow D_t \Rightarrow (D_s \times D_q)"$	imals with measure-
		ments of body tem-
		perature

Functions for Basic Observation Procedures

Observation pro-	Observation function	Example
cedure		
Object localization	$obs_{loc} :: D_d \Rightarrow D_t \Rightarrow D_s$	Location of a coal
procedure		power plant by cen-
		troid (any spatial
		point pattern)
Object prop-	$obs_{prop} :: D_d \Rightarrow D_t \Rightarrow D_q$	CO_2 emission rate
erty observation		of a power plant at
procedure		a series of times
Continuous phe-	$obs_{cphen} :: D_s \Rightarrow D_t \Rightarrow D_q$	Observation of
nomenon observa-		<i>PM</i> ₁₀ concen-
tion procedure		trations across
		Germany

Function for an ordinary Kriging procedure

Prediction	proce-	Prediction Function	Example
dure			
Ordinary procedure	kriging	$pred_{geost}$:: $GEOST$	Spatial interpolation of PM_{10} measurements using ordinary kriging.

Types of Measurement Scales and Permissible statistics

(after Stevens, 1946); statistics permissible for lower scales are also permissible for higher scale variables, but not vice-versa.

Scale Type	Permissible Statistics
Nominal	Count (number of cases), Mode,
	Contingency
Ordinal	Median, Percentiles
Interval	Mean, Standard Deviation, rank-
	order correlation, product-moment
	correlation
Ratio	Coefficient of variation

Observation windows



Meaningfulness

- Meaningfulness checks are implemented in our formalism as correspondence checks:
- Meaningful prediction is introduced based on a correspondence check between observation functions and prediction functions that ensures that there is a possible observation for each prediction.
- Meaningful aggregation is based on checking whether an observed window corresponds to the target regions of an aggregation, hence testing the condition, that the target region needs to be observed completely in case of using the sum as an aggregation function.

Air quality in Europe: EEA report 4/2012

Trends in PM $_{10}~(\mu g/m^3)$, 2001-2010, per station type



"in the diagrams a geographical bias exists towards central Europe where there is a higher density of stations" to obtain aggregate values for Europe, one needs to aggregate

predictions over Europe (block kriging)

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The limits of classes

- are traffic station air quality measurements geostatistical variables? (stationarity assumption)
- what does the sum of observed bird counts mean, in particular in case of volunteered information?
- if not meaningful, what do interpolated point pattern mark tell us?

OWL pattern



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Outlook

- this paper constrained to meaningfulness of spatio-temporal prediction and aggregation, and addressed geostatistical and point pattern data.
- Iattice data, or trajectory data were not addressed
- rasters, imagery has not been addressed
- "deeper" statistical problems include model estimation, and model selection (evaluating assumptions)
- what can we do to make our theory work (help) in practice?
- how can random variables, or variables with uncertainty, be represented in the formalism?

Conclusions

- The fringe zone between geoinformatics and spatial statistics offers several exciting challenges at the engineering, societal and scientific level, even that of information theory.
- I mentioned a few, related to activities in my group, that addressed R, interoperability, model web, and semantic reference systems (and ignored data analysis, air quality and exposure modelling, monitoring network design, land use change in Brazil, 52°North, and citizen science)
- Most of this work is completely in the open, meaning that everyone is welcome to participate!