GW framework

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Geographically Weighted Approaches

The previous exercise outlined how statistical approaches (logistic regression / Generalized Linear Models) could be used to generate probabilities of the User, Producer and Overall accuracy. These models are aspatial and because they consider all of the data in the study area they are referred to as *Global* models.

It is now possible to consider the geographically weighted extensions to these models (Brunsdon et al. 1996). They are similar in form to ordinary regression, but geographically weighted approaches use a moving window or kernel under which local regression models are computed at locations throughout the study area.

To create GW models equations 2-4 in the previous exercise were extended in the following way:

$$P(Ao = 1) = logit(b_{0(u_i,v_i)})(eqn1)$$

$$P(y_i = 1) = logit(b_{0(u_i,v_i)} + b_1 x_{1(u_i,v_i)}(eqn2)$$

$$P(x_i = 1) = logit(b_{0(u_i,v_i)} + b_1 y_{1(u_i,v_i)}(eqn3)$$

where $P(Ao = 1)$ is the overall accuracy probability at location i, x_1 and y_1 are the classified and reference data, respectively, and (u_i, v_i) is a vector of two-dimensional coordinates describing the location of i over which the coefficient estimates are assumed to vary. Thus, GW models are *local*: they are spatial dis-aggregations of *global* models and their outputs are location specific.

Critical to the operation of GW models is a moving window or kernel. The kernel moves through the study area (for example to cells in a predefined grid) and at each location computes a local model. It uses data under the kernel to construct a (local) model at that location with data weighted points further away from the kernel centre contributing less to the solution. Hence the *weighted* element in the GW framework. Thus, the kernel defines the data and weights that are used to calibrate the model at each location. The weight, w_i, associated with each location (u_i, v_i) is a decreasing function of d_i, the distance from the centre of the kernel to (u_i, v_i):

A typical kernel function for example is the *bisquare* kernel. For a given bandwidth h, this is defined by

$$f(d) = \begin{cases} \left(1 - \left(\frac{d}{h}\right)^2\right)^2 & \text{if } d < h; \\ \\ 0 & \text{otherwise.} \end{cases}$$

Here h may be defined as a fixed value, or in an adaptive way, for example to be the distance from the kth closest point in the `SpatialCrossTabs` object to $\mathbf{u}$. Gollini *et al* (2013) provide a description of common kernels shape used in GW models. Generally larger values of h result in a greater degree of spatial smoothing - having a larger window around $\mathbf{u}$ in which cross tabulations have non-zero weighting.

Here, the bandwidth was selected to include the nearest 15% of the data points - see the code and detail of this below.

GW models in R

There are a number of packages that support geographically weighted analyses in R, including `spgwr`, `GWmodel`, `gwrr` and `McSpatial`. `GWmodel` is curated and supported by the original GWR team but `spgwr` is used here.

Gollini at al (2013) provide an overview of geographically weighted approaches and provide a thorough treatment demonstrate their use, including the steps of model selection, bandwidth / kernel size optimisation, GW PCA, handling collinearity etc. The next sections deal with these stages in turn.

Set up

The code below loads the packages, the data and creates a `SpatialPointsDataFrame` variable for use as input to the GW generalized regression to determine overall accuracy. The packages can be called and the data can be loaded into R.

This can be done locally after you have set the working directory using the `setwd()` function. The example from my computer is below:

```r
library(GISTools)
library(spgwr)
setwd("/Users/geoaco/Desktop/my_docs_mac/leeds_work/workshop/datacode")
roilib <- readShapePoly("lib_clip.shp")
data <- read.csv("all_data_new2.csv")
```

Alternatively the code below loads into your working directory directly from a `RData` file also on the site.

```r
library(GISTools)
library(spgwr)
library(repmis)
source_data("http://github.com/lexcomber/LexTrainingR/blob/master/SpatialAccuracy.RData?raw=True")
```

```
## [1] "data"   "roilib"
```

And have a look at the what you have

```r
ls()
```

```
## [1] "data"   "roilib"
```

```r
head(data.frame(data))
```

```
##   PointID   East   North Urban_FS Vegetation_FS Woody_FS Grazing_FS
## 1       1 301847 3631819   0.2500         0.250    0.250       0.25
## 2       2 302491 3632155   0.0000         0.250    0.000       0.00
## 3       3 303834 3631818   0.0000         0.000    0.750       0.00
## 4       4 304480 3631008   0.2500         0.625    0.000       0.00
## 5       5 306691 3632967   0.6875         0.250    0.000       0.00
## 6       6 308175 3630784   0.0000         0.750    0.125       0.00
##   Bare_FS Boolean_FS Urban_RS Vegetation_RS Woody_RS Grazing_RS Bare_RS
## 1  0.0000          U    0.103         0.189    0.673      0.000   0.032
## 2  0.7500          B    0.256         0.036    0.387      0.000   0.321
## 3  0.2500          W    0.000         0.076    0.216      0.053   0.651
## 4  0.1250          V    0.112         0.372    0.215      0.185   0.110
## 5  0.0625          U    0.265         0.473    0.147      0.000   0.112
## 6  0.1250          V    0.000         0.365    0.312      0.143   0.175
##   Boolean_RS
## 1          V
## 2          B
## 3          W
## 4          V
## 5          V
## 6          V
```

```
library(GISTools)
# library(GWmodel)
library(spgwr)
library(repmis)
source_data("http://github.com/lexcomber/LexTrainingR/blob/master/SpatialAccuracy.RData?raw=True")
```

```
## [1] "data"   "roilib"
```

```
# have a look at the data
ls()
```

```
## [1] "data"   "roilib"
```

Now create a variable indicating where the Field data / class is equal to the Classified data / class:

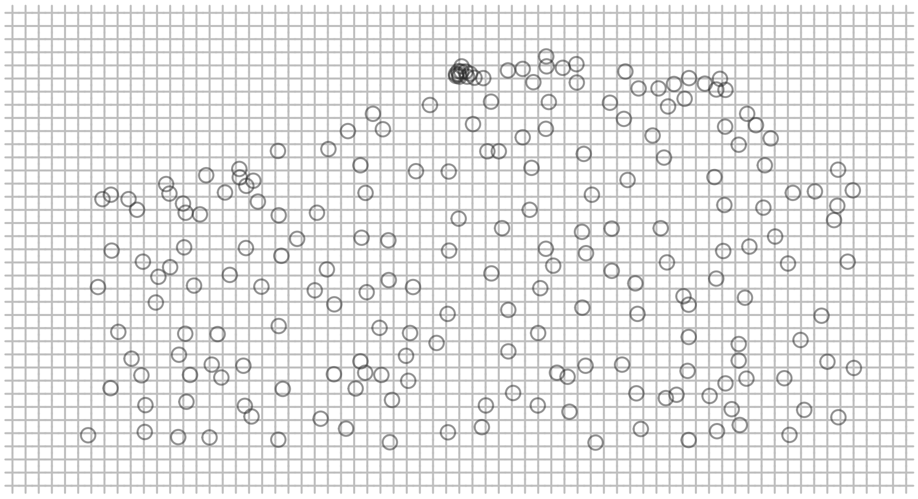
```
res <- vector(length = dim(data)[1])
for (i in 1: dim(data)[1]) {
    if (data$Boolean_RS[i] == data$Boolean_FS[i]) {
        res[i] <- 1
    }}
res.spdf <- SpatialPointsDataFrame(coords = data[,2:3], data = data.frame(res))
```

We also need to define the a logit function:

```
alogit <- function(x){exp(x)/(1+exp(x))}
```

In this case we want to calculate ;local models at each location on a 1km grid. This is crwated and mapped in the code below:

```
grid <- SpatialPoints(expand.grid(x=seq(295000,363000,by=1000),
  y=seq(3610000,3646000,by=1000)))
plot(grid, cex = 0.7, col = "grey")
plot(res.spdf, add = T, pch = 1, col = "#25252580")
```



Bandwidth specification

It is important to select the correct bandwidth or kernel size. Too small and the results will be too heterogeneous, too large and any local variation will be smoothed out. There are a number of bandwidth selection functions in `GWmodel` and the one for GW GLMs is `bw.ggwr`. One of the inputs it requires is a distance matrix, describing the distance between the data points.

```
#d.mat <- gw.dist(coordinates(res.spdf), coordinates(res.spdf))
#bw <- bw.ggwr(res~1, data = res.spdf, kernel = "bisquare",
#  adaptive = TRUE, approach = "CV", dMat = d.mat)
bw <- ggwr.sel(res~1, data = res.spdf,adapt = T, family= binomial, verbose = F)
```

```
bw
```

```
## [1] 0.9999367
```

In this case the value is 1.00 / 209 suggesting that **all** of the data should be used at each location! Harry will explain the reasons for this. So for pragmatism, the bandwidth was set to 0.15 to ensure that for each local model the nearest 3 of the data points were included:

```
bw = 0.15
```

Running the GW model: overall Accuuracy

Then the GW model can be used to generate coefficient estimates at each location which can be used to generate overall accuracy probabilities:

```
# gw.mod <- gwr.generalised(res~1, data = res.spdf, grid, bw = bw,
#  family ="poisson", kernel="bisquare",adaptive=T)
# NB the ggwr will return warnings for logistic regression - ignore them
gwr.mod <- ggwr(res~1, data = res.spdf, adapt = bw,
  fit.points = grid, family= binomial)
gwr.ov <- alogit(data.frame(gwr.mod$SDF)[,2])# Compute local P(Ao=1)
```

Mapping the outputs

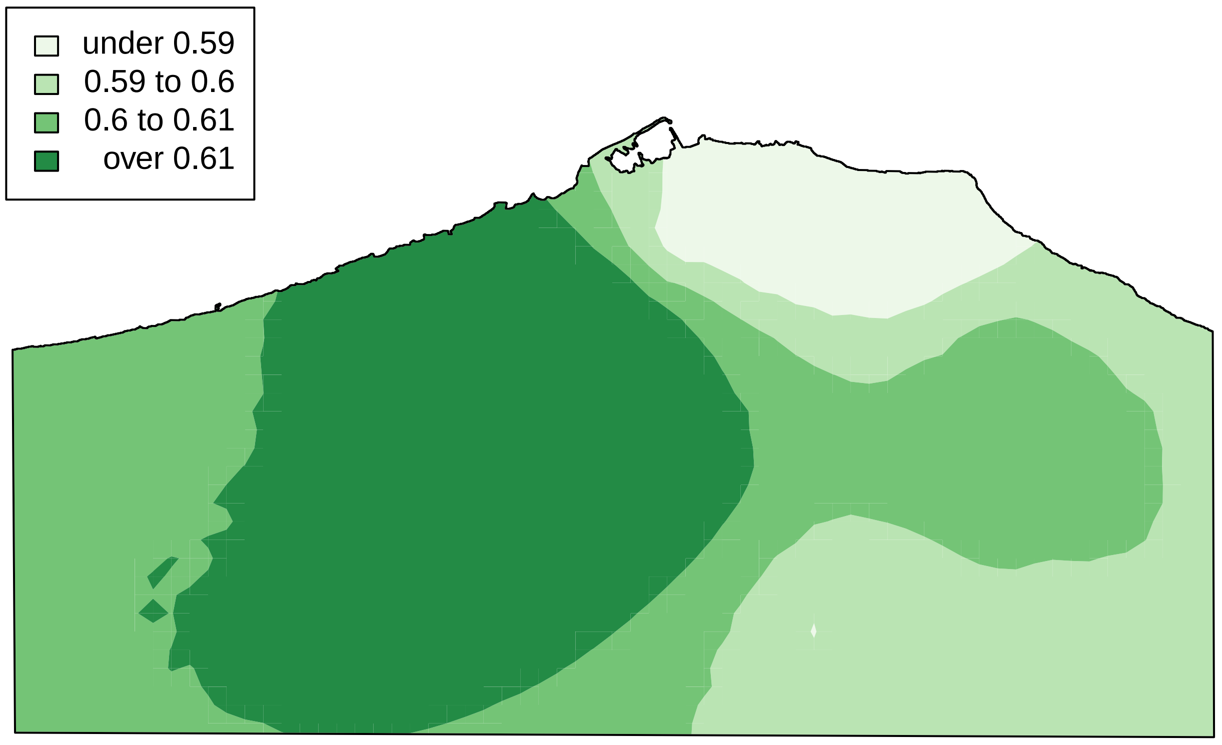
The results show only a small amount variation:

```r
summary(gwr.ov)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.5717  0.5962  0.6057  0.6053  0.6104  0.6446
```

But these can still be mapped

```r
shades = auto.shading(gwr.ov, cols=brewer.pal(4,"Greens"))
gwr.res = SpatialPixelsDataFrame(gwr.mod$SDF, data.frame(gwr.ov))
par(mar = c(0,0,0,0))
level.plot(gwr.res,shades)
lib.masker = poly.outer(gwr.res, roilib, extend = 100)
add.masking(lib.masker)
plot(roilib, add = T)
choro.legend(297000, 3650000,shades)
```



Summary

In this section you been introduced to the basics of Geographically Weighted approaches and how they can be applied to validation data that are typically collected to generate *a*spatial or *global* accuracy measures. The GW framework constructs *local* models and allows spatially distributed measures of accuracy to be generated. In the next section you will User and producer measures of accuracy and map the results.

References

Brunsdon, C.F., Fotheringham, A.S. and Charlton M. (1996). Geographically Weighted Regression - A Method for Exploring Spatial Non-Stationarity, *Geographic Analysis*, 28: 281-298.

Gollini, I., Lu, B., Charlton, M., Brunsdon, C., and Harris, P. (2013). GWmodel: an R Package for Exploring Spatial Heterogeneity using Geographically Weighted Models. *arXiv preprint arXiv*:1306.0413.