meuse_tutorial

nabil

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The following is taken from a vignette in the gstat package. gstat contains "geostatistical" functions, which can perform spatial (or, spatio-temporal) interpolations. This is particularly useful when you have data for certain points in a large area, and want some idea of how the values for that data being measured, might vary elsewhere.

In having tried to understand how work with spatial and spatio-temporal (hereafter denoted "S/T") data in R, I've realized there's a better way. First, for those looking to start, since gstat has functions that deal with spatial and S/T data, understanding how those structures work would probably be very useful when you start dealing with this package.

At least for me, there were certain aspects of this tutorial which weren't obvious when I read through it, and in the end, took a while before I felt like I had a comfortable sense of what was happening. So, I thought I could elaborate on parts which weren't immediately obvious to me. Along the way, to help myself, I thought to code it how I've become used to. Hence, the plots are all re-done in ggplot2 (with the originals alongside for comparison), and the pipe operator %>% can really help clarify steps in involved operations.

```
library(sp)
library(tidyr)
library(ggplot2)
library(magrittr, warn.conflicts = FALSE)
```

Basically, the Meuse dataset contains measurements for concentrations of different elements, over an area in the Netherlands. Run ?meuse for more info.

```
data(meuse)
class(meuse)
```

```
## [1] "data.frame"
```

```
str(meuse)
```

```
## 'data.frame':    155 obs. of  14 variables:
##  $ x      : num  181072 181025 181165 181298 181307 ...
##  $ y      : num  333611 333558 333537 333484 333330 ...
##  $ cadmium: num  11.7 8.6 6.5 2.6 2.8 3 3.2 2.8 2.4 1.6 ...
##  $ copper : num  85 81 68 81 48 61 31 29 37 24 ...
##  $ lead   : num  299 277 199 116 117 137 132 150 133 80 ...
##  $ zinc   : num  1022 1141 640 257 269 ...
##  $ elev   : num  7.91 6.98 7.8 7.66 7.48 ...
##  $ dist   : num  0.00136 0.01222 0.10303 0.19009 0.27709 ...
##  $ om     : num  13.6 14 13 8 8.7 7.8 9.2 9.5 10.6 6.3 ...
##  $ ffreq  : Factor w/ 3 levels "1","2","3": 1 1 1 1 1 1 1 1 1 1 ...
##  $ soil   : Factor w/ 3 levels "1","2","3": 1 1 1 2 2 2 2 1 1 2 ...
##  $ lime   : Factor w/ 2 levels "0","1": 2 2 2 1 1 1 1 1 1 1 ...
##  $ landuse: Factor w/ 15 levels "Aa","Ab","Ag",..: 4 4 4 11 4 11 4 2 2 15 ...
##  $ dist.m : num  50 30 150 270 380 470 240 120 240 420 ...
```

If you'll notice, there are two columns "x" and "y" in the dataset. These are the coordinates of the location which that row of the dataframe corresponds to (if the numbers seem large, don't worry, it's just Rijksdriehoek (RDH) coordinates, used in the Netherlands.)

Now, while it's easy to include spatial information, like coordinates, just in columns of a dataframe, if someone else looks at the data, it might not be obvious what all the variables in the columns represent. So, one way to deal with this is to more concretely identify the observations with the corresponding location. Here, the result is going to be a Spatial Points Data Frame. This assignment can be done like normally, except that the formula notation is used:

```r
coordinates(meuse) <- ~ x + y
class(meuse)
```

```
## [1] "SpatialPointsDataFrame"
## attr(,"package")
## [1] "sp"
```

Once that assignment is performed, then the class of the object changes accordingly.

Behind the scenes, this new Spatial*DataFrame is actually an S4 object (i.e., that's the system of OO-programming used for it in R) :

```r
str(meuse)
```

```
## Formal class 'SpatialPointsDataFrame' [package "sp"] with 5 slots
##   ..@ data       :'data.frame':  155 obs. of  12 variables:
##   .. ..$ cadmium: num [1:155] 11.7 8.6 6.5 2.6 2.8 3 3.2 2.8 2.4 1.6 ...
##   .. ..$ copper : num [1:155] 85 81 68 81 48 61 31 29 37 24 ...
##   .. ..$ lead   : num [1:155] 299 277 199 116 117 137 132 150 133 80 ...
##   .. ..$ zinc   : num [1:155] 1022 1141 640 257 269 ...
##   .. ..$ elev   : num [1:155] 7.91 6.98 7.8 7.66 7.48 ...
##   .. ..$ dist   : num [1:155] 0.00136 0.01222 0.10303 0.19009 0.27709 ...
##   .. ..$ om     : num [1:155] 13.6 14 13 8 8.7 7.8 9.2 9.5 10.6 6.3 ...
##   .. ..$ ffreq  : Factor w/ 3 levels "1","2","3": 1 1 1 1 1 1 1 1 1 1 ...
##   .. ..$ soil   : Factor w/ 3 levels "1","2","3": 1 1 1 2 2 2 2 1 1 2 ...
##   .. ..$ lime   : Factor w/ 2 levels "0","1": 2 2 2 1 1 1 1 1 1 1 ...
##   .. ..$ landuse: Factor w/ 15 levels "Aa","Ab","Ag",..: 4 4 4 11 4 11 4 2 2 15 ...
##   .. ..$ dist.m : num [1:155] 50 30 150 270 380 470 240 120 240 420 ...
##   ..@ coords.nrs : int [1:2] 1 2
##   ..@ coords     : num [1:155, 1:2] 181072 181025 181165 181298 181307 ...
##   .. ..- attr(*, "dimnames")=List of 2
##   .. .. ..$ : chr [1:155] "1" "2" "3" "4" ...
##   .. .. ..$ : chr [1:2] "x" "y"
##   ..@ bbox       : num [1:2, 1:2] 178605 329714 181390 333611
##   .. ..- attr(*, "dimnames")=List of 2
##   .. .. ..$ : chr [1:2] "x" "y"
##   .. .. ..$ : chr [1:2] "min" "max"
##   ..@ proj4string:Formal class 'CRS' [package "sp"] with 1 slot
##   .. .. ..@ projargs: chr NA
```

While accessing elements of such an objects "slots" is discouraged, the sp package comes with useful helper functions that can be used, such as bbox and coordinates. The summary function also has slightly different output:

```r
meuse %>% coordinates %>% head
```

```
##        x      y
## 1 181072 333611
## 2 181025 333558
## 3 181165 333537
## 4 181298 333484
## 5 181307 333330
## 6 181390 333260
```

```r
meuse %>% bbox
```

```
##      min    max
## x 178605 181390
## y 329714 333611
```

```r
summary(meuse)
```

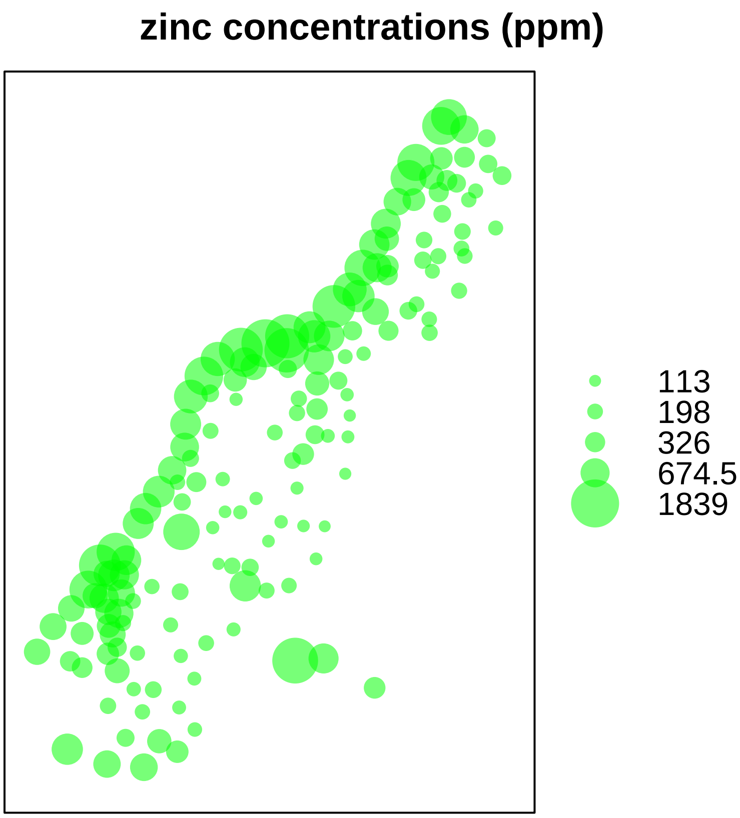
```
## Object of class SpatialPointsDataFrame
## Coordinates:
##      min    max
## x 178605 181390
## y 329714 333611
## Is projected: NA
## proj4string : [NA]
## Number of points: 155
## Data attributes:
##     cadmium           copper            lead            zinc
##  Min.   : 0.200   Min.   : 14.00   Min.   : 37.0   Min.   : 113.0
##  1st Qu.: 0.800   1st Qu.: 23.00   1st Qu.: 72.5   1st Qu.: 198.0
##  Median : 2.100   Median : 31.00   Median :123.0   Median : 326.0
##  Mean   : 3.246   Mean   : 40.32   Mean   :153.4   Mean   : 469.7
##  3rd Qu.: 3.850   3rd Qu.: 49.50   3rd Qu.:207.0   3rd Qu.: 674.5
##  Max.   :18.100   Max.   :128.00   Max.   :654.0   Max.   :1839.0
##
##       elev             dist                 om         ffreq  soil   lime
##  Min.   : 5.180   Min.   :0.00000   Min.   : 1.000   1:84   1:97   0:111
##  1st Qu.: 7.546   1st Qu.:0.07569   1st Qu.: 5.300   2:48   2:46   1: 44
##  Median : 8.180   Median :0.21184   Median : 6.900   3:23   3:12
##  Mean   : 8.165   Mean   :0.24002   Mean   : 7.478
##  3rd Qu.: 8.955   3rd Qu.:0.36407   3rd Qu.: 9.000
##  Max.   :10.520   Max.   :0.88039   Max.   :17.000
##                                     NA's   :2
##     landuse       dist.m
##  W      :50   Min.   :  10.0
##  Ah     :39   1st Qu.:  80.0
##  Am     :22   Median : 270.0
##  Fw     :10   Mean   : 290.3
##  Ab     : 8   3rd Qu.: 450.0
##  (Other):25   Max.   :1000.0
##  NA's   : 1
```

Typically, to just access the data, I coerce the object to a dataframe with as.data.frame, which can be a lot quicker and cleaner than alternatives:

```
meuse_df <- cbind( attr(meuse, "data"), meuse@coords) # just coerce to df
```

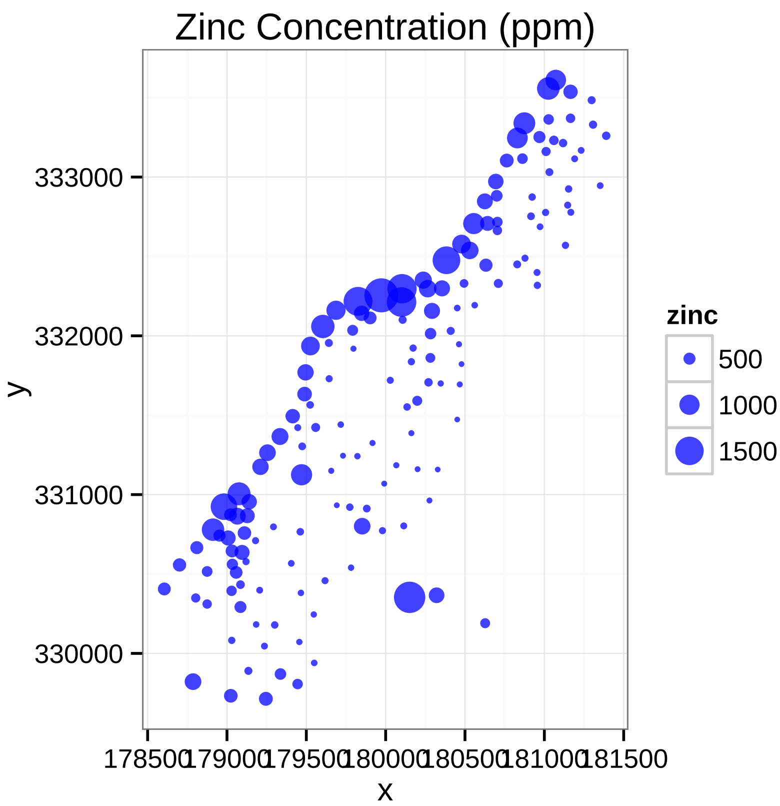
The sp package comes with special built-in graphing functions, such as "bubble":

```
# bubble chart
bubble(meuse, "zinc", col = c("#00ff0088", "#00ff0088"),
       main="zinc concentrations (ppm)")
```



The equivalent can also be made using ggplot:

```
# I think the blue stands out better against the white background
meuse %>% as.data.frame %>%
  ggplot(aes(x, y)) + geom_point(aes(size=zinc), color="blue", alpha=3/4) +
  ggtitle("Zinc Concentration (ppm)") + coord_equal() + theme_bw()
```




```
## Project the data from Rijksdriehoek (RDH) (Netherlands topographical) map
## coordinates to Google Map coordinates; RDH coordinates have an EPSG code of
## 28992 and Google map coordinates have an EPSG code of 3857

# But from the documentation of proj4string: Note that only "+proj=longlat" is
# accepted for geographical coordinates, which must be ordered (eastings,
# northings). So use sp

# plan: convert rdh to longlat, then assign longlat, then transform to rdh
# TODO: incorporate this into a post on using ggmap with spatial data.
library(rgdal)
```

```
## rgdal: version: 0.8-16, (SVN revision 498)
## Geospatial Data Abstraction Library extensions to R successfully loaded
## Loaded GDAL runtime: GDAL 1.11.0, released 2014/04/16
## Path to GDAL shared files: /Users/nabilabd/Library/R/3.1/library/rgdal/gdal
## Loaded PROJ.4 runtime: Rel. 4.8.0, 6 March 2012, [PJ_VERSION: 480]
## Path to PROJ.4 shared files: /Users/nabilabd/Library/R/3.1/library/rgdal/proj
```

```
ESPG <- make_EPSG()
ESPG[which(ESPG$code == 28992), ]
```

```
##       code                     note
## 3504 28992 # Amersfoort / RD New
##
## 3504 +proj=sterea +lat_0=52.15616055555555 +lon_0=5.38763888888889 +k=0.9999079 +x_0=155000 +y_0=463
```

```r
rdh_proj <- ESPG[which(ESPG$code == 28992), "prj4"]

#proj4string(meuse) = "+proj=longlat +datum=WGS84"
```

Along with the meuse dataset is one called meuse.grid. Later on in the interpolation, it's used as locations to predict concentrations for. At first, it's just a regular dataframe like meuse was:

```r
data(meuse.grid)
summary(meuse.grid)
```

```
##        x                y              part.a           part.b      
##  Min.   :178460   Min.   :329620   Min.   :0.0000   Min.   :0.0000  
##  1st Qu.:179420   1st Qu.:330460   1st Qu.:0.0000   1st Qu.:0.0000  
##  Median :179980   Median :331220   Median :0.0000   Median :1.0000  
##  Mean   :179985   Mean   :331348   Mean   :0.3986   Mean   :0.6014  
##  3rd Qu.:180580   3rd Qu.:332140   3rd Qu.:1.0000   3rd Qu.:1.0000  
##  Max.   :181540   Max.   :333740   Max.   :1.0000   Max.   :1.0000  
##       dist        soil     ffreq   
##  Min.   :0.0000   1:1665   1: 779  
##  1st Qu.:0.1193   2:1084   2:1335  
##  Median :0.2715   3: 354   3: 989  
##  Mean   :0.2971                    
##  3rd Qu.:0.4402                    
##  Max.   :0.9926                    
```

```r
meuse.grid %>% str
```

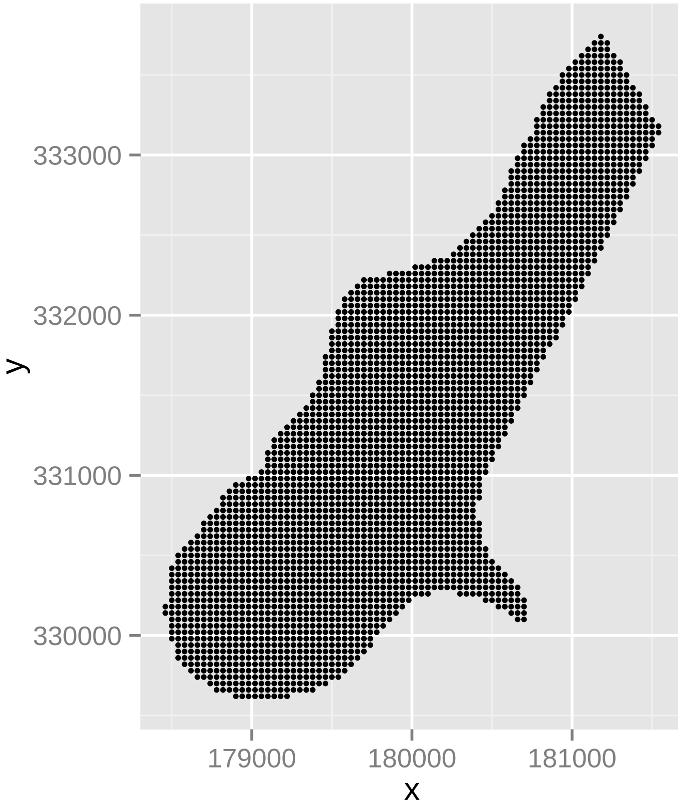
```
## 'data.frame':    3103 obs. of  7 variables:
##  $ x     : num  181180 181140 181180 181220 181100 ...
##  $ y     : num  333740 333700 333700 333700 333660 ...
##  $ part.a: num  1 1 1 1 1 1 1 1 1 1 ...
##  $ part.b: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ dist  : num  0 0 0.0122 0.0435 0 ...
##  $ soil  : Factor w/ 3 levels "1","2","3": 1 1 1 1 1 1 1 1 1 1 ...
##  $ ffreq : Factor w/ 3 levels "1","2","3": 1 1 1 1 1 1 1 1 1 1 ...
```

```r
meuse.grid %>% class
```

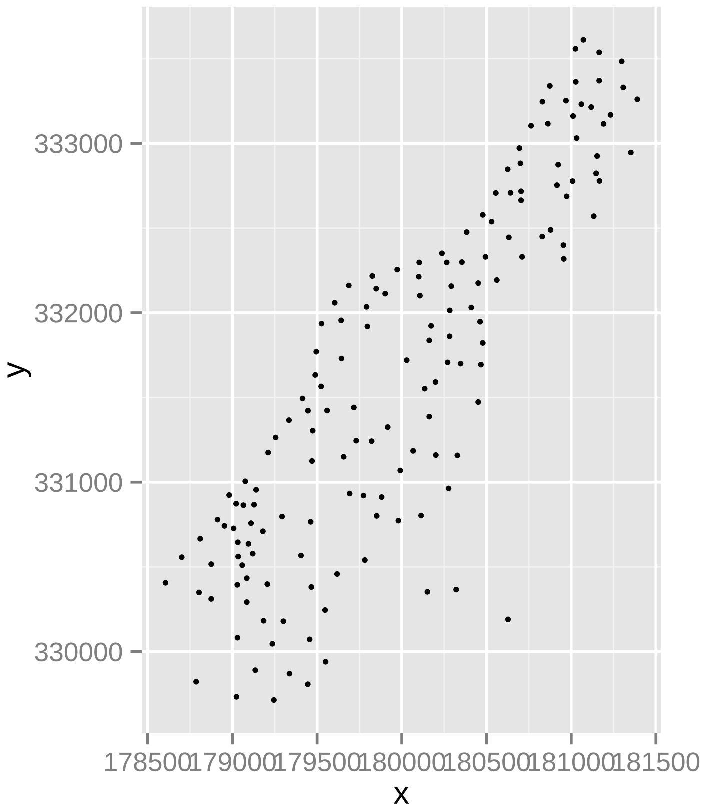
```
## [1] "data.frame"
```

To better see the gridded nature of the data, we can just plot it:

```r
# this is clearly gridded over the region of interest
meuse.grid %>% as.data.frame %>%
  ggplot(aes(x, y)) + geom_point(size=1) + coord_equal()
```




```r
# to compare, recall the bubble plot above; those points were what there were
# values for. this is much more sparse
meuse %>% as.data.frame %>%
  ggplot(aes(x, y)) + geom_point(size=1) + coord_equal()
```



These two plots pretty much summarize our interpolation problem: given values at the locations in the latter plot, we want to interpolate over all values in the former plot.

And just as before, we specify that the x and y columns are actually coordinates for the observations. Here, though, we can also manually specify that meuse.grid actually cotains a grid of points. Although this might not appear to change anything if you only inspect the class, the attributes of the object do change (to see that, just check the attributes before and after identifying it as gridded).

```
coordinates(meuse.grid) = ~x+y
gridded(meuse.grid) = TRUE
meuse.grid %>% class
```

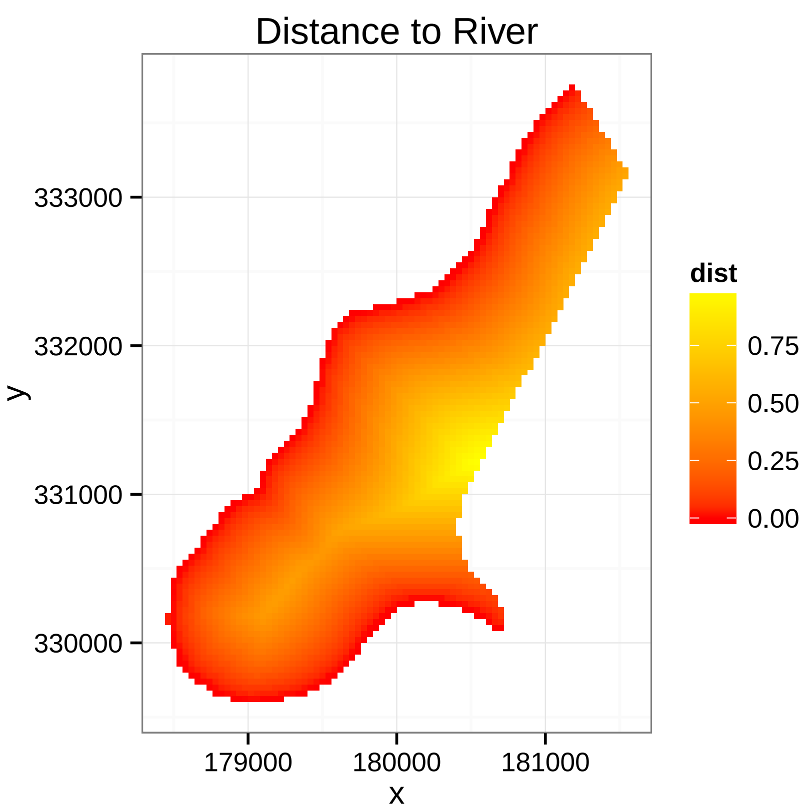
```
## [1] "SpatialPixelsDataFrame"
## attr(,"package")
## [1] "sp"
```

More plotting

```
image(meuse.grid["dist"])
title("distance to river (red=0)")
```

distance to river (red=0)

```r
# ggplot version
meuse.grid %>% as.data.frame %>%
  ggplot(aes(x, y)) + geom_tile(aes(fill=dist)) +
  scale_fill_gradient(low = "red", high="yellow") + coord_equal() + theme_bw() +
  ggtitle("Distance to River")
```



Alternatively, instead of using tiles, one could go Seurat-style and call geom_point() with small size (but, just note that scale_color_gradient goes with points, and scale_fill_gradient with tiles).

Kriging interpolation of remaining points

To recap up to this point: we have values at some points, and want to interpolate over an entire grid. In this case, we can use gstat's kriging functions. In particular, we'll just start off with the simple "krige" for now.

```
library(gstat)

zinc.idw <- krige(zinc ~ 1, meuse, meuse.grid)
```

```
## [inverse distance weighted interpolation]
```

```
zinc.idw %>% class
```

```
## [1] "SpatialPixelsDataFrame"
## attr(,"package")
## [1] "sp"
```

```
zinc.idw %>% as.data.frame %>% head
```

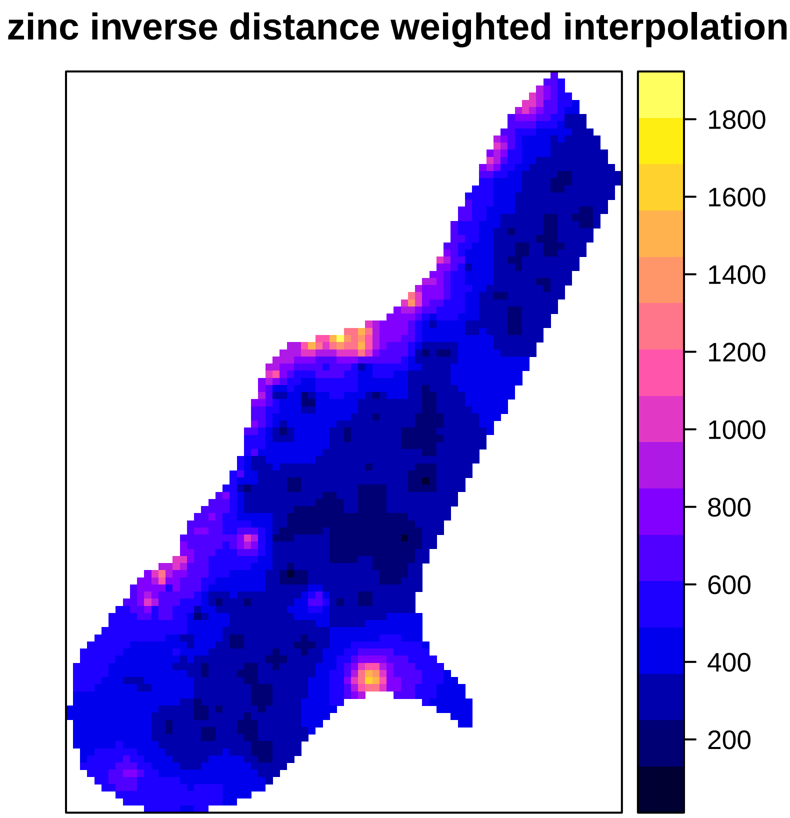
```
##        x      y var1.pred var1.var
## 1 181180 333740  633.6864       NA
## 2 181140 333700  712.5450       NA
## 3 181180 333700  654.1617       NA
## 4 181220 333700  604.4422       NA
## 5 181100 333660  857.2558       NA
## 6 181140 333660  755.5061       NA
```

Here, there are a couple things to note. First, the function takes a "formula" argument. Since we want to interpolate for values of zinc, we would use "ordinary", or "simple", kriging, in which case we use the notation "[variable] ~ 1". The second argument is the where the values of that variable being interpolated, come from. The third is the region of interest, such as a grid of spatial locations we want estimated predictions for.

The result of the kriging is a data frame with coordinates (x and y), predicted values of the variable ("var1.pred"), and variance of the predictions ("var1.var"). (Aside: I'm not really sure why in this example, there are NA's for the prediction variance; I think it's because a variogram wasn't supplied to form the predictions from. However, I'm almost not clear how there can be predictions without that variogram, but I haven't studied much of the theory behind this yet).

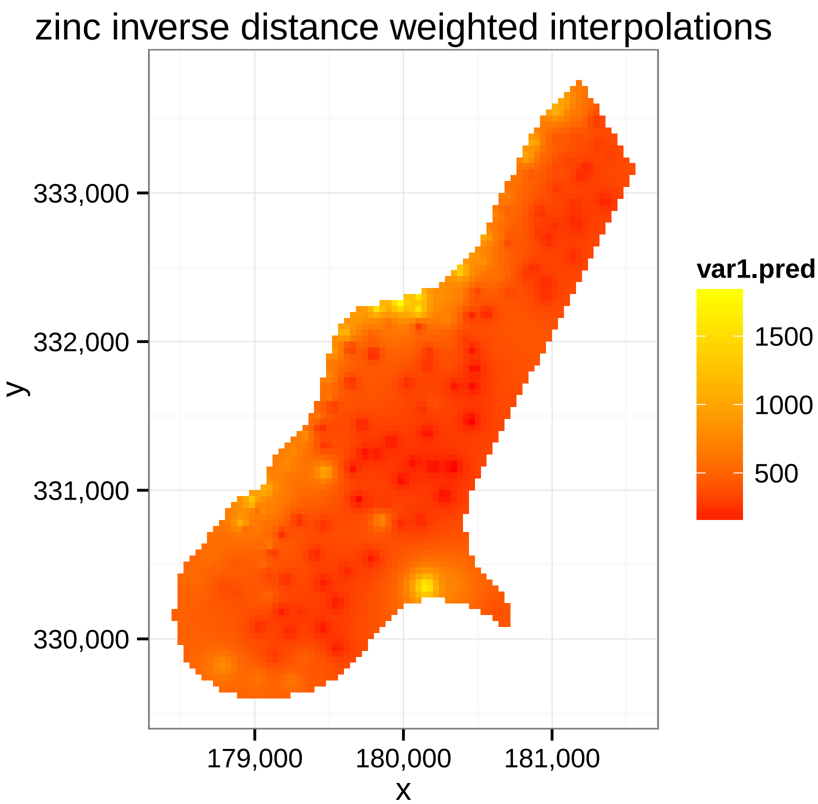
These results, again, can be graphed with the sp package's functions, or otherwise with ggplot2:

```
spplot(zinc.idw["var1.pred"], main="zinc inverse distance weighted interpolations")
```



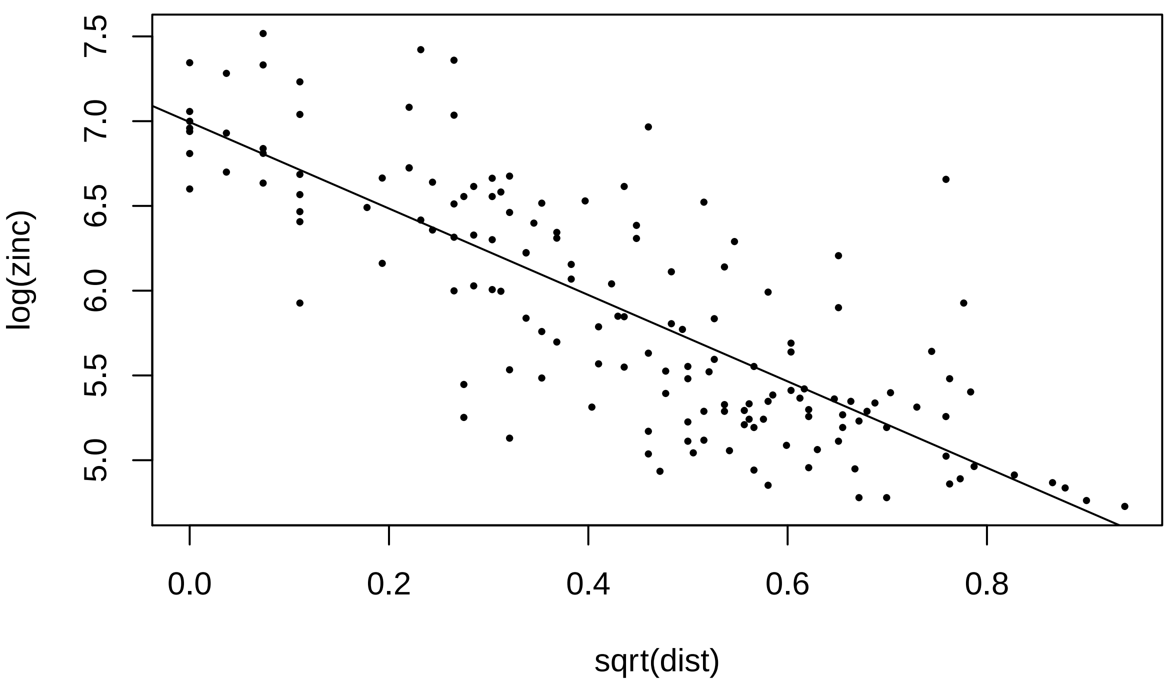

```r
#same spplot with ggplot
library(scales)

zinc.idw %>% as.data.frame %>%
  ggplot(aes(x=x, y=y, fill=var1.pred)) + geom_tile() + theme_bw() +
  coord_equal() + scale_fill_gradient(low = "red", high="yellow") +
  ggtitle("zinc inverse distance weighted interpolations") +
  scale_x_continuous(labels=comma) + scale_y_continuous(labels=comma)
```



One advantage of ggplot2 in this case is the amount of control over the color scheme (as well as other aspects of the plot). In the example above, I stuck to the red-to-yellow scale used earlier. Although, note that here, red doesn't represent "0" anymore.

```
# graphical check of hypothesis from above graphs
plot(log(zinc) ~ sqrt(dist), data=meuse, pch=16, cex=.5)
abline(lm(log(zinc) ~ sqrt(dist), meuse))
```



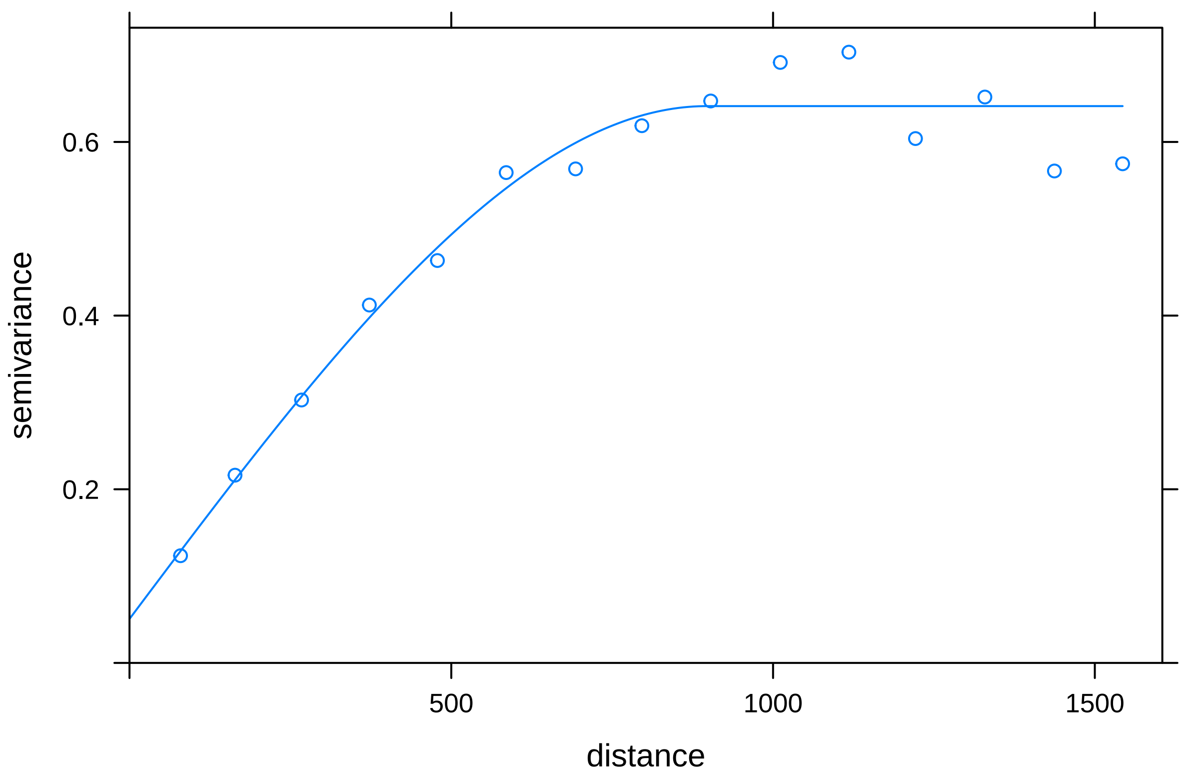
```r
# or with ggplot:
# meuse %>% as.data.frame %>%
#   ggplot(aes(sqrt(dist), log(zinc))) + geom_point() +
#   geom_smooth(method="lm", se=FALSE)
```

Variogram plotting

As alluded to earlier, it's often helpful when performing kriging to also have a variogram (or, semi-variogram) model fit to the data. For an excellent introduction to variograms, see Allison Lassiter's website.

Basically, while we did interpolate using a relationship for zinc, we might want to explore how log(zinc) varies over space. For this, we can plot a variogram. First, the code, then more explanation about what the code does.

```r
# inspect variation of log(zinc) by distance (i.e., from the river)
lzn.vgm <- variogram(log(zinc)~1, meuse) # calculates sample variogram values
lzn.fit <- fit.variogram(lzn.vgm, model=vgm(1, "Sph", 900, 1)) # fit model
plot(lzn.vgm, lzn.fit) # plot the sample values, along with the fit model
```



In the first line, we merely calculate a sample variogram. This involves several things, as can be seen by inspecting the actual object:

```r
lzn.vgm
```

```
##     np       dist     gamma dir.hor dir.ver   id
## 1   57   79.29244 0.1234479       0       0 var1
## 2  299  163.97367 0.2162185       0       0 var1
## 3  419  267.36483 0.3027859       0       0 var1
```

```
## 4  457  372.73542 0.4121448       0       0 var1
## 5  547  478.47670 0.4634128       0       0 var1
## 6  533  585.34058 0.5646933       0       0 var1
## 7  574  693.14526 0.5689683       0       0 var1
## 8  564  796.18365 0.6186769       0       0 var1
## 9  589  903.14650 0.6471479       0       0 var1
## 10 543 1011.29177 0.6915705       0       0 var1
## 11 500 1117.86235 0.7033984       0       0 var1
## 12 477 1221.32810 0.6038770       0       0 var1
## 13 452 1329.16407 0.6517158       0       0 var1
## 14 457 1437.25620 0.5665318       0       0 var1
## 15 415 1543.20248 0.5748227       0       0 var1
```

```
lzn.vgm %>% class
```

```
## [1] "gstatVariogram" "data.frame"
```

```
lzn.fit %>% class
```

```
## [1] "variogramModel" "data.frame"
```

The first column, np, says how many point pairs were within distance "dist" (if those numbers look like a lot, recall that although meuse has only 155 rows, there are 155 * 154 / 2 = 11,935 point pairs; see the plot above with the points graphed). If we plot this object itself, we just get the sample variogram, without any fit to it (try it!).

To perform a fit, we call the fit.variogram function, and pass it two parameters: a variogram object, and a model we want to fit the data to. With the model specified, the function would find the optimal (in some sense) parameters for that model to fit the data.

In this tutorial, a spherical model is used. The book Applied Spatial Data Analysis with R (ASDAR) has the complete list of variogram models one can use. And while the functional forms of those models aren't included, a more graphical/qualitative display of characteristics for different variogram models, is available by calling the function: show.vgms().

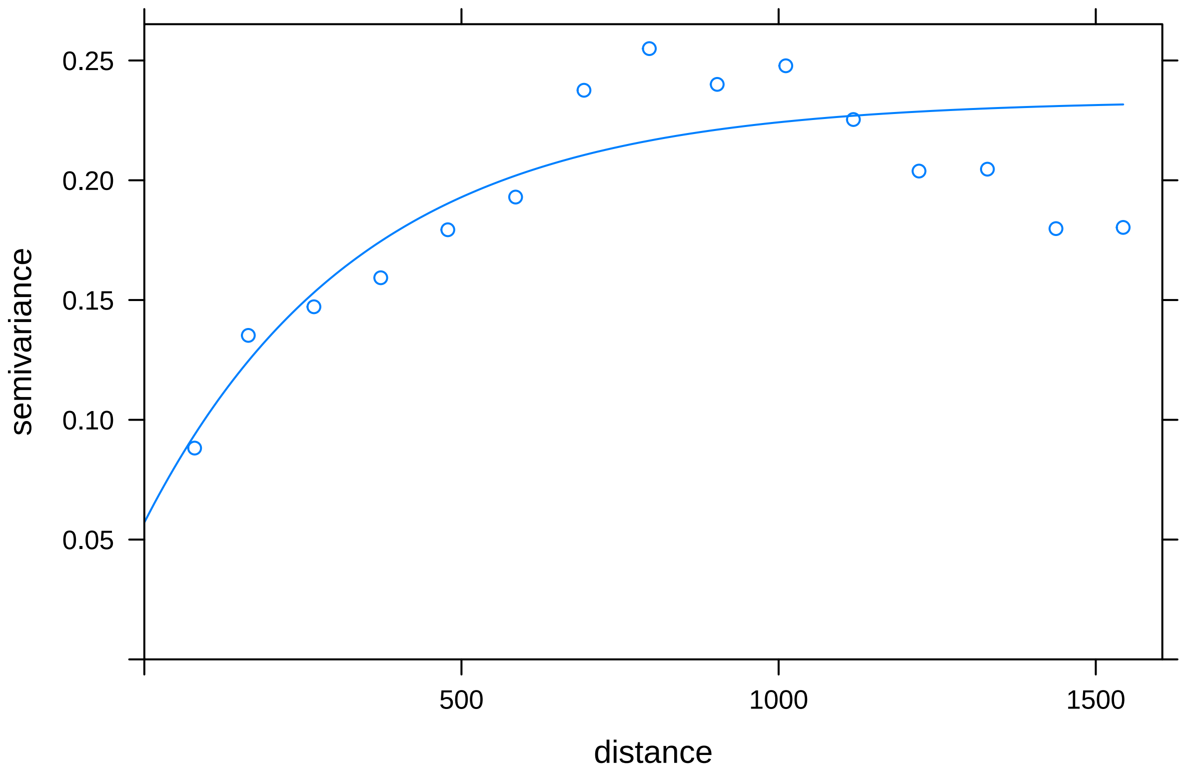
Now if you plot the variogram and the fit, you (surprise!) get both together.

But we might not like that model. So we could try to see how log(zinc) varies with the square root of distance. This time, we'll try an exponential model. Otherwise, everything is pretty much the same as before:

```
# inspect variation of log(zinc) by square root of distance
lznr.vgm <- variogram(log(zinc) ~ sqrt(dist), meuse)
lznr.fit <- fit.variogram(lznr.vgm, model=vgm(1, "Exp", 300, 1))
lznr.fit %>% class
```

```
## [1] "variogramModel" "data.frame"
```

```
plot(lznr.vgm, lznr.fit)
```



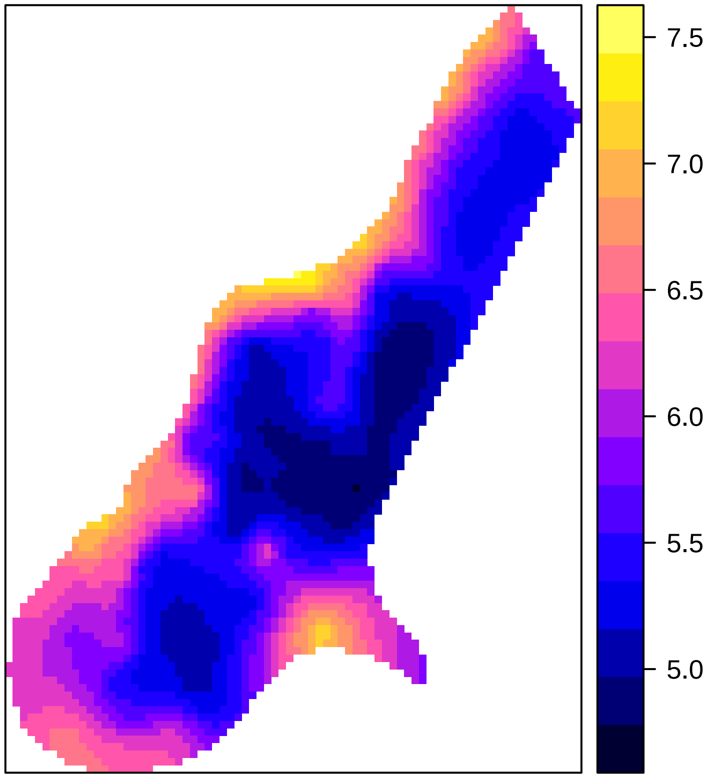
Section 6: Kriging

question: how do kriging results vary if no model specified? question: how does kriging happen when no projection specified? This seems to be opposed to the meuse tutorial. note: here, interpolation done on gridded SPDF, but this time, result is another SPDF (unlike when not specifying vgm model). Also, there are values for var1.var in the output (which seems to be variance of the prediction).

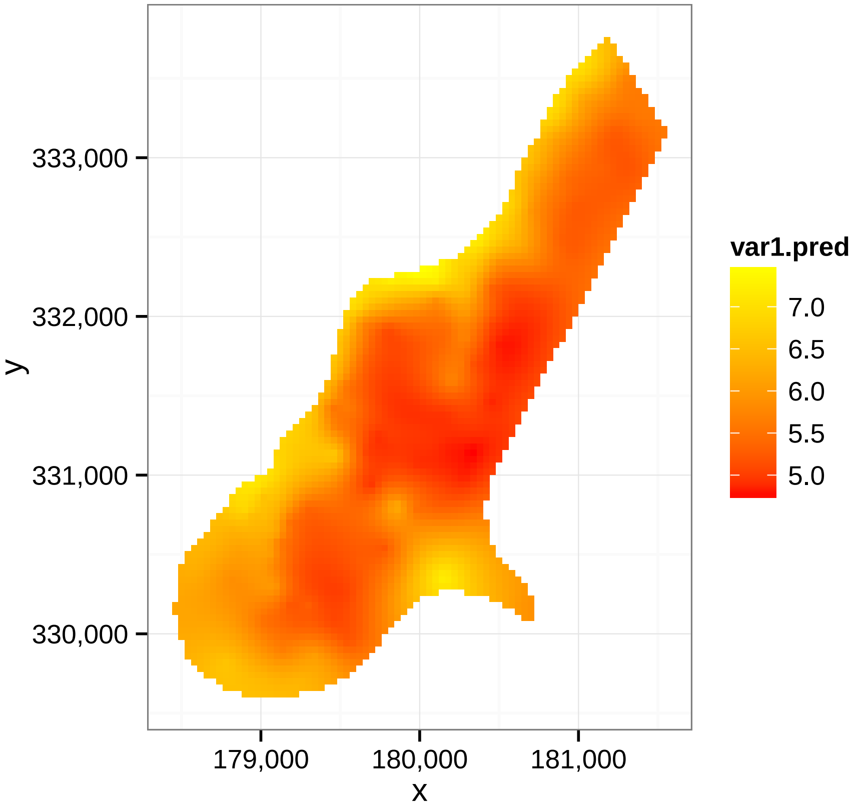
```
lzn.kriged <- krige(log(zinc) ~ 1, meuse, meuse.grid, model=lzn.fit)
```

```
## [using ordinary kriging]
```

```
# sp plotting
spplot(lzn.kriged["var1.pred"])
```




```r
# kriging results in ggplot
lzn.kriged %>% as.data.frame %>%
  ggplot(aes(x=x, y=y)) + geom_tile(aes(fill=var1.pred)) +
  coord_equal() + scale_fill_gradient(low = "red", high="yellow") +
  scale_x_continuous(labels=comma) + scale_y_continuous(labels=comma) +
  theme_bw()
```

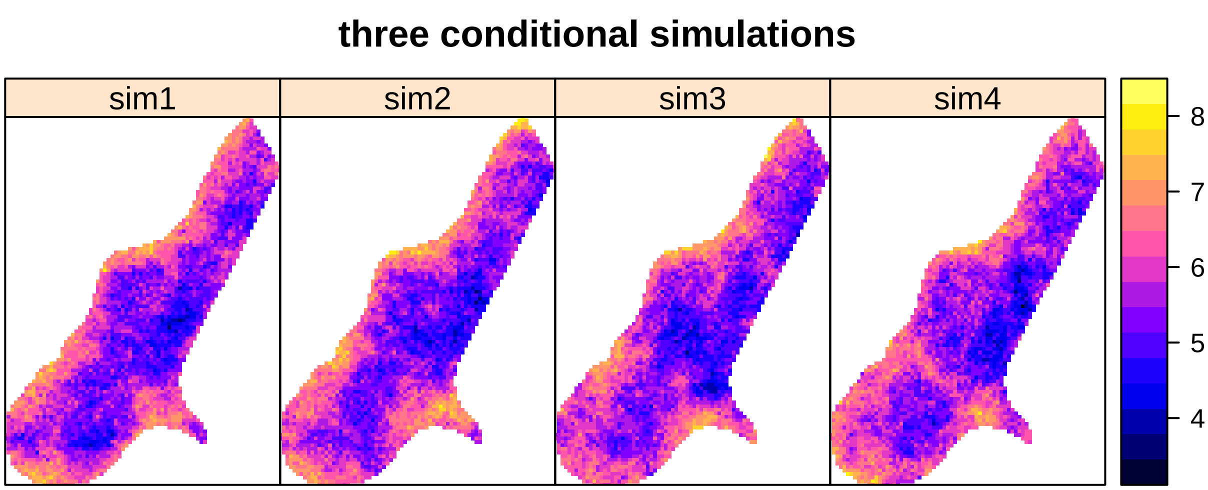


Section 7: Conditional Simulations

```
lzn.condsim <- krige(log(zinc)~1, meuse, meuse.grid, model=lzn.fit,
                     nmax=30, nsim=4)
```

```
## drawing 4 GLS realisations of beta...
## [using conditional Gaussian simulation]
```

```
# sp plotting
spplot(lzn.condsim, main="three conditional simulations")
```



```r
# with ggplot2. (no need to call components with "@" or "attr(., "data"), e.g.)
#lzn_cond_df <- cbind(attr(lzn.condsim, "data"), attr(lzn.condsim, "coords"))
lzn.condsim %>% as.data.frame %>%
  gather(sim, value, sim1:sim4) %>%
  ggplot(aes(x=x, y=y)) + geom_tile(aes(fill=value)) +
  facet_grid(.~sim) + coord_fixed(ratio = 1) +
  scale_x_continuous(labels=comma) + scale_y_continuous(labels=comma) +
  scale_fill_gradient(low = "red", high="yellow") +
  ggtitle("Three conditional simulations") + theme_bw()
```