sdcSpatial: Privacy protected density maps

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useR! 2019, July 11 2019

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sdcSpatial has methods for:

- Creating a raster map: sdc_raster for pop density, value density and mean density, using the excellent raster package by Hijmans (2019).
- Finding out which locations are sensitive: plot_sensitive, is_sensitive
- Adjusting raster map for protecting data: protect_smooth, protect_quadtree
- Removing sensitive locations.

Who am I?

- Statistical consultant, Data Scientist @cbs.nl / Statistics NL
- Expertise:
  - **R programming**
  - Data Cleaning with R
  - **Data visualization**
  - Complex networks analysis
  - @edwindjonge / https://github.com/edwindj

What is SN / CBS?

Statistics Netherlands is producer of all main official statistics in the Netherlands:

- Stats on Demographics, economy (GDP), education, environment, agriculture, Finance etc.
- Part of the European Statistical System, ESS.

Motivation for `sdcSpatial`

- ESS has European Code of Statistical Practice (predates GDPR, European law on Data Protection):
  no individual information may be revealed.

Sdc in `sdcSpatial`?

SDC = “Statistical Disclosure Control”

Collection of statistical methods to:

- Check if data is safe to be published
- Protect data by slightly altering (aggregated) data
  - adding noise
  - shifting mass
- Most SDC methods operate on records.
- **`sdcSpatial` works upon locations.**

Let’s create a `sdc_raster`

Creation:

```
library(sdcSpatial)
unemployed <- sdc_raster( dwellings[c("x", "y")]
                        , dwellings$unemployed
                        , r = 500 # raster resolution of 500m
                        , min_count = 10 # min support
                        )
```

What is it about?

```
print(unemployed)
```

```
## logical sdc_raster object:
##    resolution: 500 500 ,  max_risk: 0.95 , min_count: 10
##    mean sensitivity score [0,1]:  0.4249471
```

What is sensitivity?

Binary score (`logical`) per raster cell indicating if it's unsafe to publish.

Calculated:

a) Per location (x_i, y_i) (raster cell)

b) Using risk function `disclosure_risk` $r(x, y) \in [0, 1]$. How accurate can an attacker estimate the value of an individual?
If $r(x_i, y_i) >$ `max_risk` then (x_i, y_i) is sensitive.

c) Using a minimum number of observations.
If count$_i$ < `min_count`, then (x_i, y_i) is sensitive.

Type of raster density maps:

Density can be area-based:

- **number of people** per square (`unemployed$value$count`): population density.
- **(total) value** per square (`unemployed$value$sum`): number of unemployed per square.

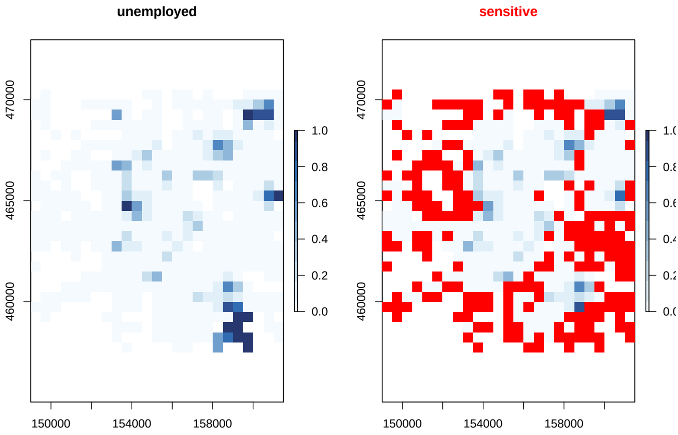
Or density can population-based:

- **Mean value** per square (`unemployed$value$mean`): probability of being unemployed per square.

Note: All density types are valid, but (total) value per square strongly interacts with population density. (see https://xkcd.com/1138).

Plotting a `sdc_raster`

```
plot(unemployed, "mean")
```



how to improve?

Options:

a) Use a coarser raster: `sdc_raster`.

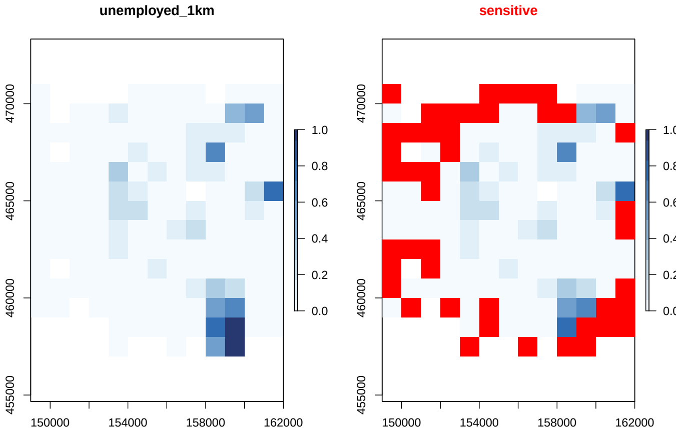
b) Apply Spatial smoothing: `protect_smooth` method by Wolf and Jonge (2018), Jonge and Wolf (2016).

c) Aggregate with a Quad tree: `protect_quadtree` method by Suñé et al. (2017).

d) Remove sensitive locations: `remove_sensitive`.

Option: coarser raster

```
unemployed_1km <- sdc_raster( dwellings[c("x", "y")]
                            , dwellings$unemployed, r =1e3)
plot(unemployed_1km, "mean")
```



Option: Coarsening

Pros

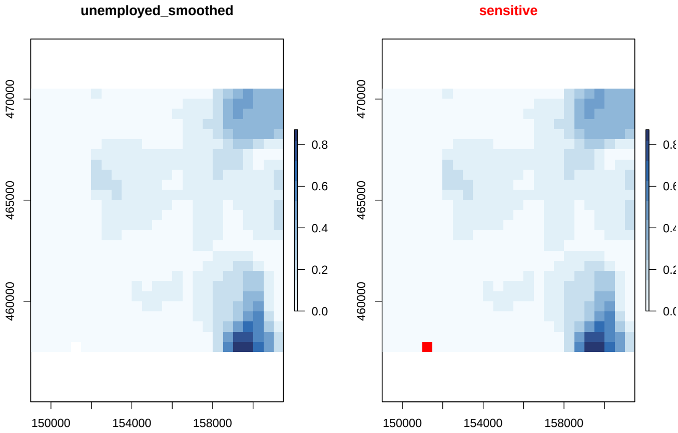
- Simple and easy explainable

Cons

- Detailed spatial patterns are removed
- visually unattractive: “Blocky”

Option: KDE-smoothing

```
unemployed_smoothed <- protect_smooth(unemployed, bw = 1500)
plot(unemployed_smoothed, "mean")
```



Options: KDE-smoothing

Pro's

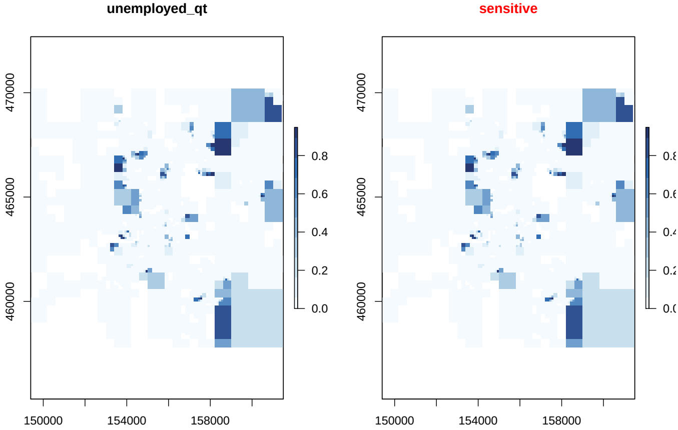
- Often enhances spatial pattern visualization, removing spatial noise.
- Makes it a density map and used as source for e.g. contour map.

Con's

- Does not remove all sensitive values (depends on bandwidth `bw`)
- A fixed band width is used for all locations: may remove detailed patterns...
  spatial processes often have location dependent band widths. (= future work)

Option: Quad tree

```
unemployed_100m <- sdc_raster( dwellings[c("x","y")], dwellings$unemployed
                              , r = 100) # use a finer raster
unemployed_qt <- protect_quadtree(unemployed_100m)
plot(unemployed_qt)
```



Option: Quad tree

Pro

- Adapts to data density
- Adjusts until no sensitive data is left.

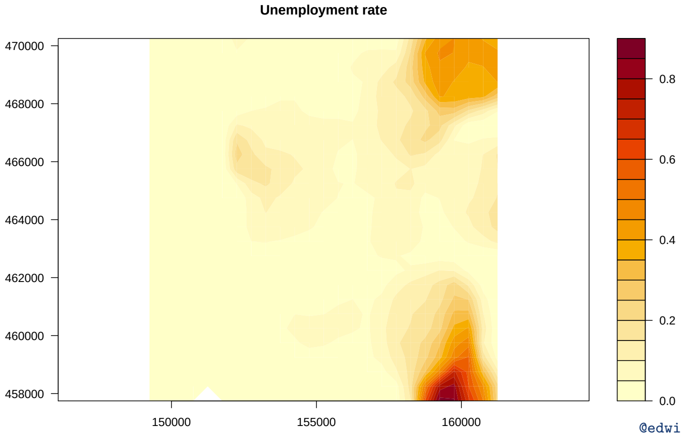
Cons

- Visually: “Blocky” / “Mondrian-like” result.

Publish: visual interpolation

So in 5 lines we create a visual attractive map that is safe:

```r
unemployed <- sdc_raster(dwellings[c("x","y")], dwellings$unemployed, r=500)
unemployed_smoothed <- protect_smooth(unemployed, bw = 1500)
unemployed_safe <- remove_sensitive(unemployed_smoothed)
mean_unemployed <- mean(unemployed_safe)
raster::filledContour(mean_unemployed, main="Unemployment rate")
```



The end

Thank you for your attention!

Questions?

Curious?

```
install.packages("sdcSpatial")
```

Feedback and suggestions?

https://github.com/edwindj/sdcSpatial/issues

References

Hijmans, Robert J. 2019. *Raster: Geographic Data Analysis and Modeling*. https://CRAN.R-project.org/package=raster.

Jonge, Edwin de, and Peter-Paul de Wolf. 2016. “Spatial Smoothing and Statistical Disclosure Control.” In *Privacy in Statistical Databases*, edited by Josep Domingo-Ferrer and Mirjana Pejić-Bach, 107–17. Springer.

Suñé, E., C. Rovira, D. Ibáñez, and M. Farré. 2017. “Statistical Disclosure Control on Visualising Geocoded Population Data Using Quadtrees.” http://nt17.pg2.at/data/x_abstracts/x_abstract_286.docx.

Wolf, Peter-Paul de, and Edwin de Jonge. 2018. “Spatial Smoothing and Statistical Disclosure Control.” In *Privacy in Statistical Databases - Psd 2018*, edited by Josep Domingo-Ferrer and Francisco Montes Suay. Springer.