

Spatio-temporal geostatistics using `gstat`



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1 Introduction

Since `gstat` package version 1.0-0, a dependency of `gstat` on the R package `spacetime` was introduced, allowing the code in `gstat` to exploit spatio-temporal data structures from that package. This vignette describes the possibilities and limitations of the package for spatio-temporal geostatistics.

To understand some of the possibilities and limitations, some knowledge of the history of the software is needed. The original `gstat` software (Pebesma and Wesseling, 1998) was a standalone computer *program* written in around 25,000 lines of C code, and would do geostatistical modelling, prediction and simulation. The `gstat` R package (Pebesma, 2004) consisted mostly of an R interface to this C code, together with convenience functions to use R's modelling interface (formula's, see `?lm`) and graphic capabilities (trellis graphics in package `lattice` to show cross variogram as matrix plots; interaction with variogram clouds using base plots).

Starting 2003, a group of programmers developed a set of classes and methods for dealing with spatial data in R (points, lines, polygons, grids), which was supported by the publications of the well-known ASDAR book (Bivand et al. 2008; see also <http://www.asdar-book.org/>) and helped convergence in the user community, with in 2011 over 2000 subscribers on the `r-sig-geo` mailing list. Package `gstat` was one of the first packages that adopted and benefited from these classes.

To realize a particular idea, writing code in C typically takes about 10-20 times as long as writing it in R. C code can be more efficient, gives more control over memory usage, but is also more error prone—mistakes in C code make an R session crash, something that is hard to do when writing R code.

The original C code of `gstat` (Pebesma and Wesseling, 1998) provides all kriging varieties (universal, ordinary, simple; univariable, or multivariable as in cokriging) for two- or three-dimensional data. When the spatial domain is constrained to two dimensions (and this might cover over 99% of the use cases!), the third dimension might be used to represent time. As such, the *metric* variogram model, which allows for geometric anisotropy definition in three dimensions, can be used for spatio-temporal kriging. When defining the three-dimensional variogram as the sum of 2 or more nested variogram (summed)

models, one can choose anisotropy coefficients for a single model such that this model is *effectively* zero in some directions, e.g. in space *or* in time; this allows one to approximate the so-called space-time sum model. It should be noted that at the C code there is no knowledge whether a third dimension represents space, or time. As such, particular characteristics of time cannot be taken care of.

Since the second half of 2010, the development of an R package **spacetime** started. It provides methods and classes for spatio-temporal data, and builds on the spatial data classes in **sp** and time series classes in **xts**. This document will explain how data in this form, and methods provided by this package, can be used for spatio-temporal geostatistics.

We will work with a data set with air quality (PM10) measurements over germany, taken from rural background stations available in the data sets provided by the European Environmental Agency.

```
> library(spacetime)
> rm(list = ls())
> data(air)
> ls()

[1] "DE"          "DE_NUTS1" "air"        "dates"      "stations"
```

2 Variography

2.1 Temporal autocorrelation and cross correlation

We will look into a subset of the data, ranging from 2005 to 2010, and remove stations that have only missing values in this period:

```
> if (!exists("rural"))
+   rural = STFDF(stations, dates, data.frame(PM10 = as.vector(air)))
> rr = rural[, "2005::2010"]
> unsel = which(apply(as(rr, "xts"), 2, function(x) all(is.na(x))))
> r5to10 = rr[-unsel,]
> summary(r5to10)
```

Object of class STFDF

with Dimensions (s, t, attr): (53, 1826, 1)

[[Spatial:]]

Object of class SpatialPoints

Coordinates:

	min	max
coords.x1	6.28107	14.78617
coords.x2	47.80847	54.92497

Is projected: FALSE

proj4string :

[+init=epsg:4326 +proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs
+towgs84=0,0,0]

Number of points: 53

[[Temporal:]]

	Index	timeIndex
Min.	:2005-01-01	Min. :2558

```

1st Qu.:2006-04-02    1st Qu.:3014
Median :2007-07-02    Median :3470
Mean   :2007-07-02    Mean   :3470
3rd Qu.:2008-09-30    3rd Qu.:3927
Max.   :2009-12-31    Max.   :4383
[[Data attributes:]]
      PM10
Min.   : 0.560
1st Qu.: 9.275
Median :13.852
Mean   :16.261
3rd Qu.:20.333
Max.   :269.079
NA's   :21979

```

Next, we will (rather arbitrarily) select four stations, which have the following labels:

```

> rn = row.names(r5to10@sp)[4:7]
> rn

[1] "DEBE056" "DEBE032" "DEHE046" "DENW081"

```

In the following, autocorrelation functions are computed and plotted. The resulting plot is shown in Figure 1.

```

> par(mfrow=c(2,2))
> # select 4, 5, 6, 7
> for(i in rn)
+   acf(na.omit(r5to10[i,]), main = i)
> par(mfrow=c(1,1))

```

Auto- and cross correlations can be computed when a multivariate time series object is passed to `acf`:

```

> acf(na.omit(as(r5to10[rn,], "xts")))

```

The resulting plot is shown in Figure 2. From these graphs one should be able to observe the following

- autocorrelations for lag 0 are always 1
- cross correlations for lag 0 are not always 1
- cross correlations can be asymmetric, meaning that when $\rho_{AB}(h)$ is the correlation between $Z(s_A, t)$ and $Z(s_B, t + h)$,

$$\rho_{AB}(h) = \rho_{BA}(-h) \neq \rho_{AB}(-h)$$

with s_A and s_B the two stations between which a cross correlation is computed, and h the (directional!) lag between the series.

```

> par(mfrow=c(2,2))
> # select 4, 5, 6, 7
> rn = row.names(r5to10@sp)[4:7]
> for(i in rn)
+     acf(na.omit(r5to10[i,]), main = i)

```

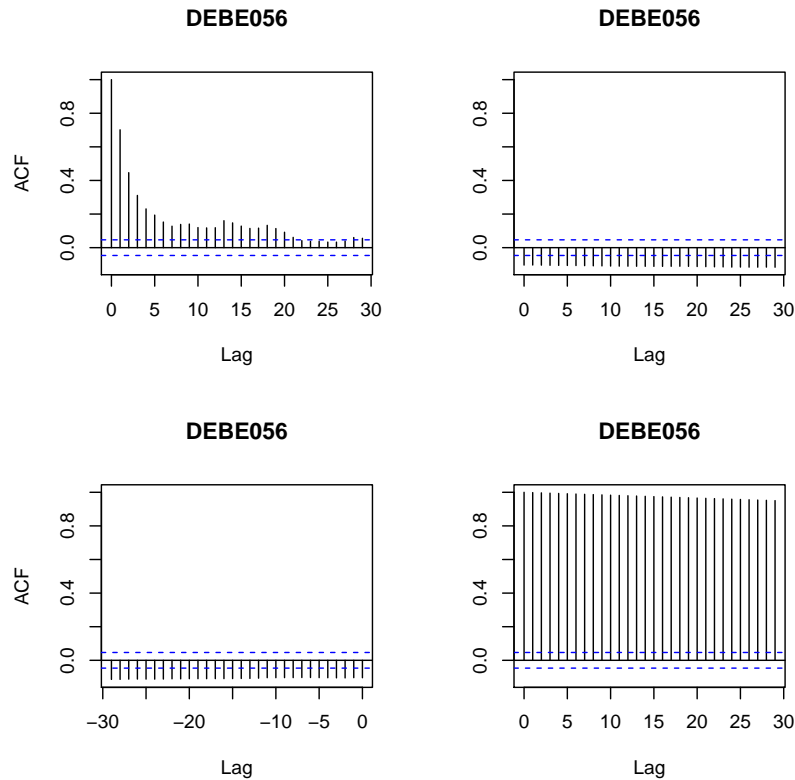


Figure 1: Autocorrelations for PM10; time lag unit in days.

The plot further more shows that for these four stations the asymmetry is not very strong, but that cross correlations are fairly strong and of a similar form of autocorrelations.

This kind of plot does not work very well in layouts of e.g. 10 x 10 sub-plots; `acf` automatically chooses 4 x 4 as the maximum a single plot. To try this out, do a 7 x 7 plot

```

> acf(na.omit(as(r5to10[4:10,], "xts")))

```

and note that here we see in the last figure (DESH & DESN04) a pair of plots with nearly no cross correlation. This might have to do with the spatial distance between these two stations:

```

> library(sp)
> print(spDists(r5to10[4:10,]@sp), digits=3)

```

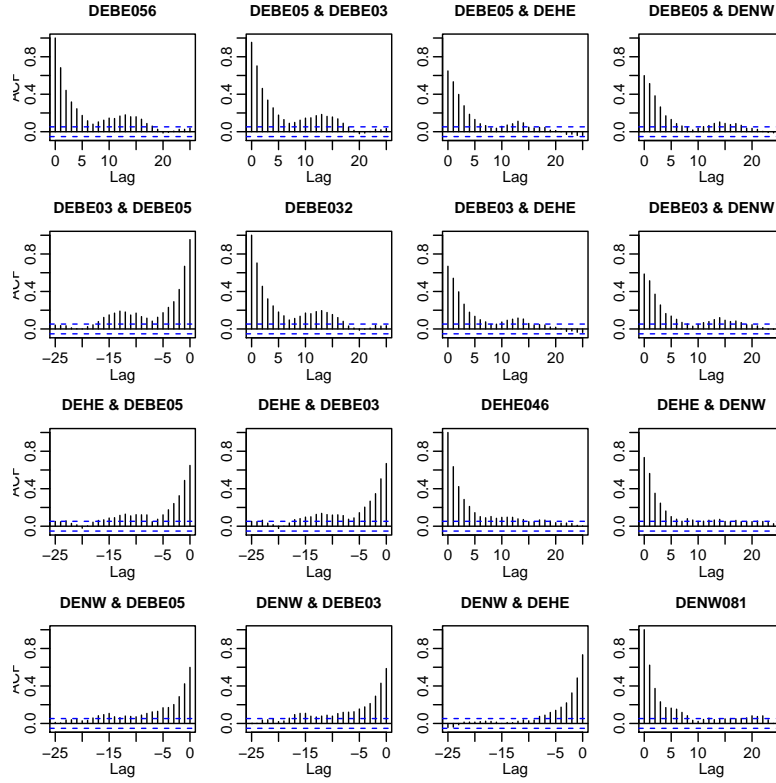


Figure 2: autocorrelations (diagonal) and cross correlations (off-diagonal) for the four stations selected; time lag unit in days.

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]
[1,]	0.0	28.8	344	468	292	235	135
[2,]	28.8	0.0	317	440	269	231	131
[3,]	343.6	317.3	0	150	309	282	285
[4,]	467.9	439.7	150	0	336	432	430
[5,]	291.7	268.5	309	336	0	438	362
[6,]	235.5	231.0	282	432	438	0	101
[7,]	134.6	130.9	285	430	362	101	0

(What is the spatial distance between stations DESH and DESN04?)

2.2 Spatial correlation, variograms

In the next steps, we will sample 100 time instances randomly,

```
> rs = sample(dim(r5to10)[2], 100)
```

we select these instances as a `SpatialPointsDataFrame` and add a time index to them. After this we bind them together in a single `SpatialPointsDataFrame` which has a time index `ti`:

```
> lst = lapply(rs, function(i) { x = r5to10[,i]; x$ti = i; x} )
> pts = do.call(rbind, lst)
```

Then, we can compute the pooled variogram

```
> library(gstat)
> v = variogram(PM10~ti, pts[!is.na(pts$PM10),], dx=0)
```

and plot it (Figure 3):

```
> # plot(v, fit.variogram(v, vgm(1, "Exp", 200, 1)))
> vmod = fit.variogram(v, vgm(1, "Exp", 200, 1))
> plot(v, vmod)
```

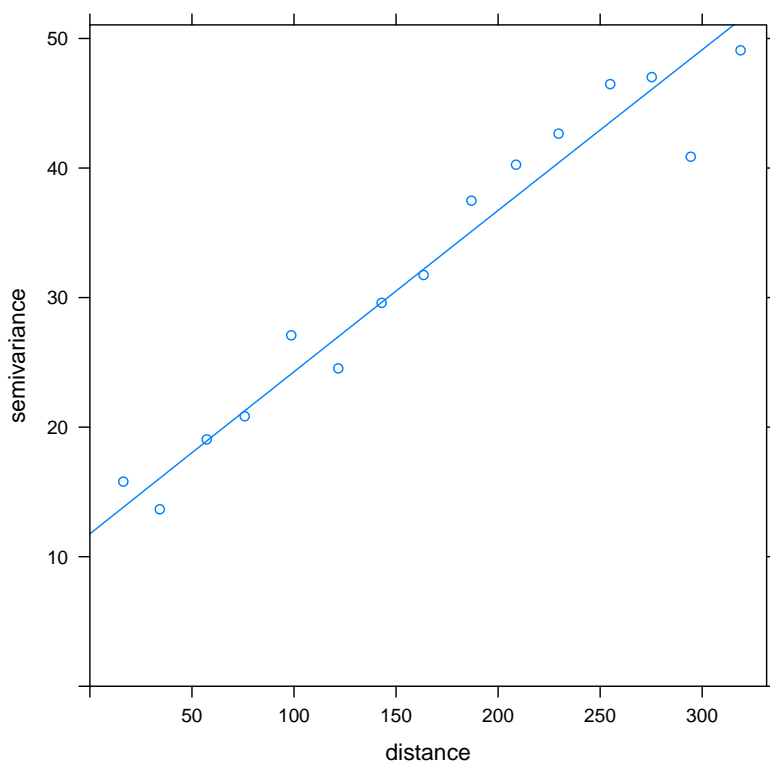


Figure 3: sample spatial variogram, averaged over 100 randomly chosen time steps

The fitted model is this:

```
> vmod
```

	model	psill	range
1	Nug	11.764	0.00
2	Exp	2905.415	23176.57

One should note that the fit is rather poor, and not forget that we only have 53 stations selected. The time resolution is rich (1862 days) but the number of stations is small:

```
> dim(r5to10)
```

```
      space      time variables
      53      1826           1
```

We can fit a spatio-temporal variogram the usual way, by passing an object of class `STFDF` (Pebesma, 2012):

```
> vv = variogram(PM10~1, r5to10, width=20, cutoff = 200, tlags=0:5)
```

Alternatively, if this takes too long, a temporal subset can be taken, e.g. using the first 200 days:

```
> vv = variogram(PM10~1, r5to10, width=20, cutoff = 200, tlags=0:5)
```

taking random days from the full period will lead to the a wrong assumption that every time index increment reflect a constant lag increase. As an alternative, we will here load the precomputed S/T variogram:

```
> data(vv)
```

Plotting this object can be done in several ways, two 2D-plots are shown in Figure 4 and a 3D wireplot is shown in Figure 7:

```
> plot(vv)
> plot(vv, map = FALSE)
```

2.3 Fitting a spatio-temporal variogram model

At first, we try to fit a metric model with spatio-temporal anisotropy:

```
> metricVgm <- vgmST("metric",
+                   joint=vgm(50, "Exp", 100, 0),
+                   stAni=50)
> metricVgm <- fit.StVariogram(vv, metricVgm)
```

As numerical criterion to judge the goodness of fit of model and sample variogram, the root-mean-squared-difference between the surfaces can be obtained by:

```
> attr(metricVgm, "optim")$value

[1] 60.60854
```

The final model can be plotted with the sample variogram (Figure 5):

```
> plot(vv, metricVgm)
```

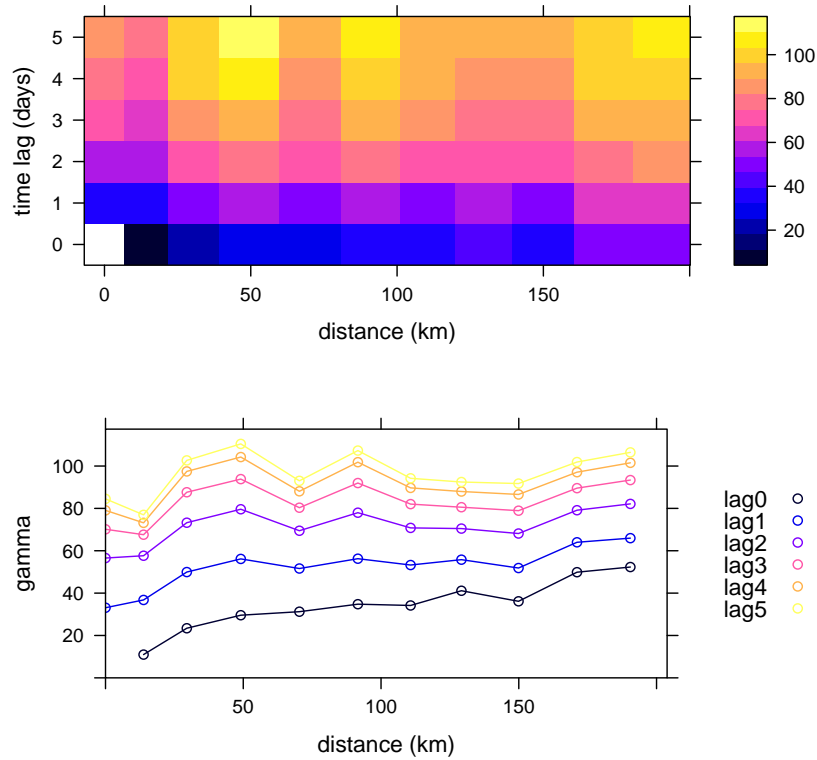


Figure 4: Spatio-temporal sample variogram map (top) and sample variograms for each time lag (bottom); both figures depict the information of object `vv`.

Now, let us try to fit and plot a separable model (Figure 6):

```
> sepVgm <- vgmST("separable",
+               space=vgm(0.9,"Exp", 123, 0.1),
+               time =vgm(0.9,"Exp", 2.9, 0.1),
+               sill=100)
> sepVgm <- fit.StVariogram(vv, sepVgm, method = "L-BFGS-B",
+               lower = c(10,0,0.01,0,1),
+               upper = c(500,1,20,1,200))
```

To compare this model with the previous one, we look at the optimized root-mean-squared-differences between the two surfaces and plot sample and both models:

```
> attr(sepVgm, "optim")$value
[1] 46.39099
> plot(vv, list(sepVgm, metricVgm))
```

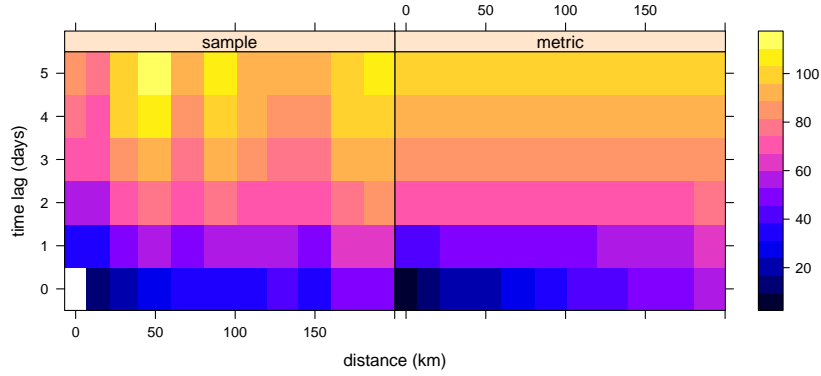



Figure 5: Sample variogram map (left) and fitted metric model (right).

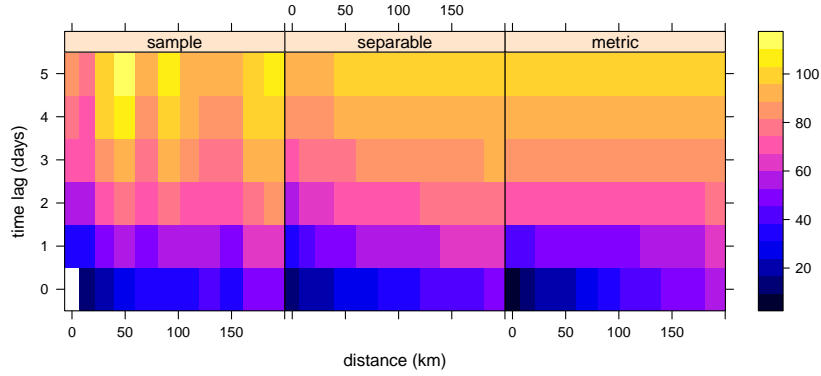


Figure 6: Sample variogram map (left), fitted separable model (middle) and fitted metric model (right).

A wireframe (3D) plot of sample variogram and fitted variogram models can be obtained e.g. by

```
> library(lattice)
> plot(vv, list(sepVgm, metricVgm), all=T, wireframe=T, zlim=c(0,120),
+       zlab=NULL,
+       xlab=list("distance (km)", rot=30),
+       ylab=list("time lag (days)", rot=-35),
+       scales=list(arrows=F, z = list(distance = 5)))
```

which is shown in Figure 7. Further spatio-temporal model definitions can be found in the help pages of `fit.StVariogram` and `variogramSurface`. The demo `stkrige` presents further examples and illustrates an interactive 3D-plot of sample variogram and the fitted variogram model. An interactive variogram exploration web-tool is available at <http://giv-graeler.uni-muenster.de:3838/spacetime/>.

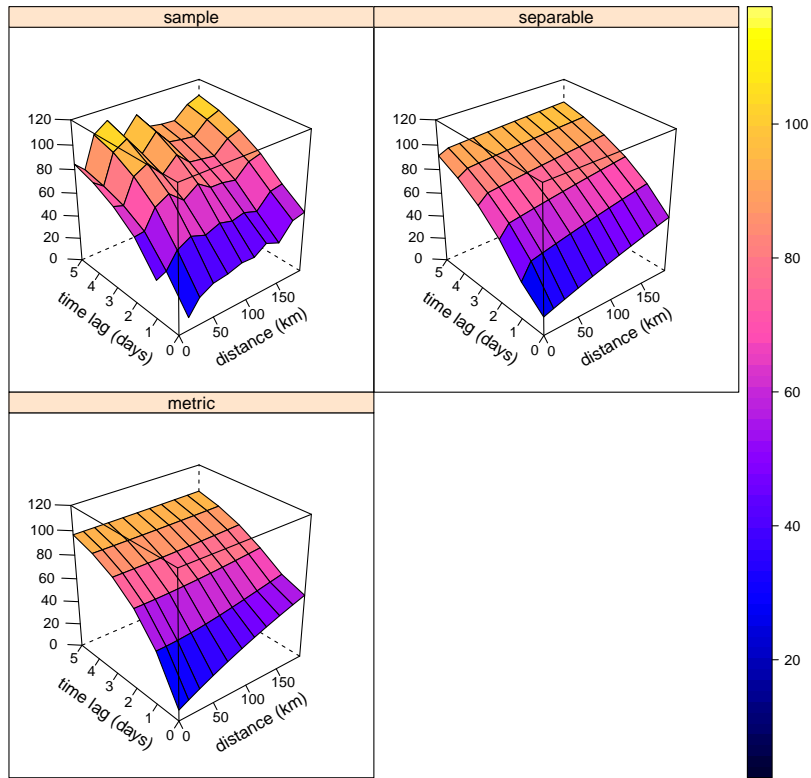


Figure 7: Wireframe plots of sample and fitted space-time variograms.

3 Spatio-temporal prediction

The vignette in package `spacetime` gives an example of using the `gstat` function `krigeST` for spatio-temporal kriging of the Irish wind data. The `krigeST` function uses global kriging, but only needs to invert the purely spatial and purely time covariance matrices in the separable case.

For more generic spatio-temporal kriging where space is two-dimensional, one could use `krige`, defining the observations and prediction locations as three-dimensional data sets, see for an example

```
> demo(gstat3D)
```

It needs to be pointed out that in that case, the time (typically the third dimension) needs to be numeric, and three-dimensional anisotropy needs to be defined properly (see `?vgm`).

In case the data set is too large for global kriging, one could try to use local kriging, and select data within some distance, or by specifying `nmax` (the nearest n observations). In both cases, it is advisable to transform time such that one can use an *isotropic* variogram model in the three dimensions, as only in that case the nearest n observations correspond to the n most correlated observations. `krigeST` provides a solution where a `bufferNmax`-times larger neighbourhood is evaluated within the covariance model and the strongest correlated `nmax` neighbours are selected.

An additional consideration is that in space-time, observations may not be regularly spaced. In some cases, the nearest n observations may come from a single measurement location, which may lead to sharp jumps/boundaries in the interpolated values. This might be solved by using larger neighbourhoods, or by setting the `omax` in `krige` or `gstat` calls to the neighbourhood size to select *per octant* (this should be combined with specifying `maxdist`).

References

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