STAT 551

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Vignette 1 - Spatial dependence and visualization for polygon level data - of House Hold Income in Harris County

Goal

Living in Houston, we all know that there are some segregations for residents with different economic status. For example, people making more money will live in the areas of which the hosing price is higher, and vice versa.

Can we make sure whether this phenomenon exists? This question can be answered by using some methods in spatial statistics.

First of all, the census dataset we are using here is from https://www.kinderudp.org/ (https://www.kinderudp.org/).

In [58]:
```
rm(list=ls())
library("rgdal")
library("dplyr")
library("data.table")
library("gstat")
library("tidyr")
library("spgwr")
library("spdep")
library("ggplot2")

# read datasets
censusData_bg <- data.table::fread("/Users/manchongleong/Desktop/STAT551/C
urated/Cen2010Harris_BG_v01.csv",
                    colClasses = c(GeoID10_bg="chatacher",
                                   stfips="character",
                                   county="character",
                                   tract="character")) %>%
  dplyr::rename(GEOID10=GeoID10_bg)
# read census boundary
censusBoundary <- rgdal::readOGR(dsn="/Users/manchongleong/Desktop/STAT55
1/",
                          layer="tl_2010_48_bg10")
# only get the records in Harris County
censusBoundary.harris <- censusBoundary[grepl(c("201"),
                                     censusBoundary@data$COUNTYFP10), ]
```

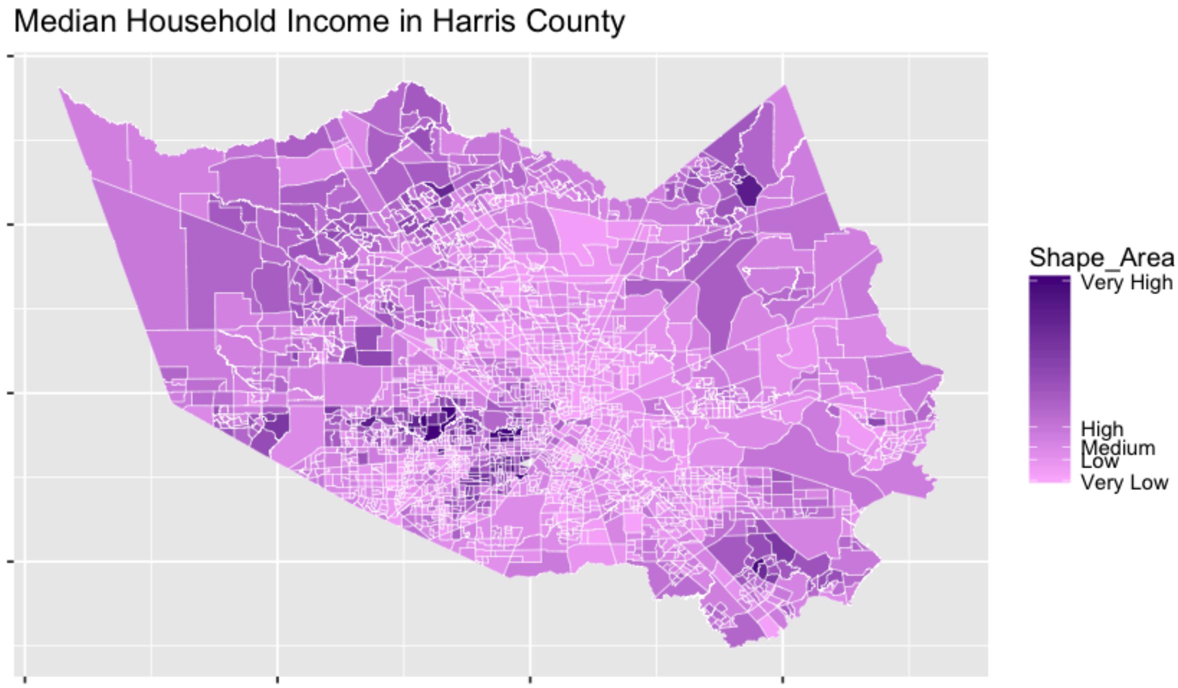
```
OGR data source with driver: ESRI Shapefile
Source: "/Users/manchongleong/Desktop/STAT551", layer: "tl_2010_48_bg10"
with 15811 features
It has 15 fields
Integer64 fields read as strings:  OBJECTID
```

The dataset we are using here is 2010 census data in blockgroup level.

In [59]:
```
# merge boundary with census data
censusBoundary.harris <- censusBoundary.harris %>%
  merge(censusData_bg, by="GEOID10")

censusBoundary.harris@data$id <- rownames(censusBoundary.harris@data)

# remove na
censusBoundary.harris_clean <- censusBoundary.harris[!(is.na(censusBoundar
y.harris@data$MedHHinc)), ]

# might have outliers, create another dataset without outlier
# outside 1.5 times the interquartile
# range above the upper quartile and bellow the lower quartile
censusBoundary.harris_clean_rm_ol <- censusBoundary.harris_clean[!(censusB
oundary.harris_clean@data$MedHHinc %in% boxplot(censusBoundary.harris_clea
n@data$MedHHinc, plot=FALSE)$out), ]
```

In [61]:

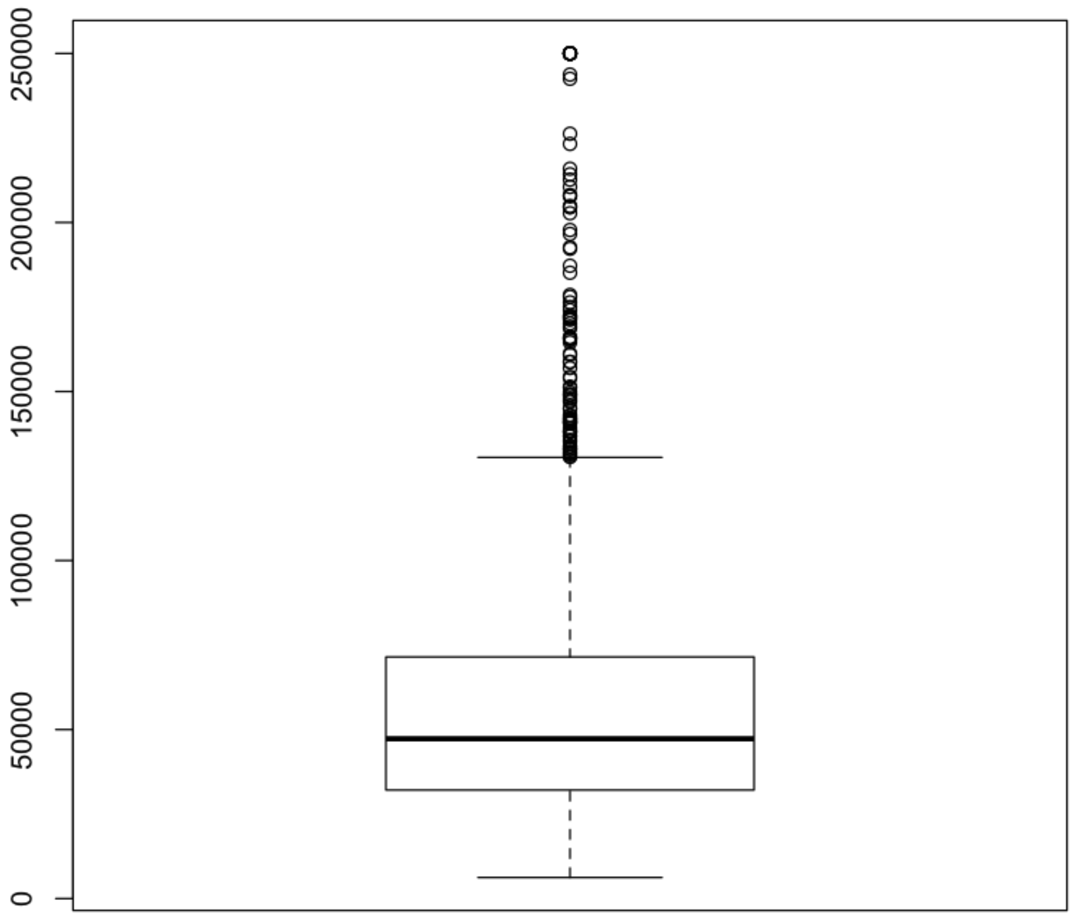
```
# convert a spatial object into data.frame
HarrisCty.tidy <- ggplot2::fortify(censusBoundary.harris_clean, region="i
d")

HarrisCty.tidy_merge <- merge(HarrisCty.tidy, censusBoundary.harris_clean@
data, by="id")

map_HarrisCty <- ggplot(data=HarrisCty.tidy_merge, aes(long,lat,group=grou
p,fill=MedHHinc)) +
  geom_polygon() +
  geom_path(color = "white", size=0.1) +
  scale_fill_gradient(low = "plum1", high = "purple4",
                      breaks = quantile(censusBoundary.harris_clean@data$M
edHHinc),
                     labels=c("Very Low", "Low", "Medium", "High", "Very H
igh")) +
  coord_equal() +
  theme(axis.title = element_blank(), axis.text = element_blank()) +
  labs(title = "Median Household Income in Harris County", fill = "Median
 Household Income")

map_HarrisCty
```



Except for couple blockgroups, the colors of the others are so light! Seems like the Median Household income in those outliers are far higher than the others.

We can check it with boxplot.

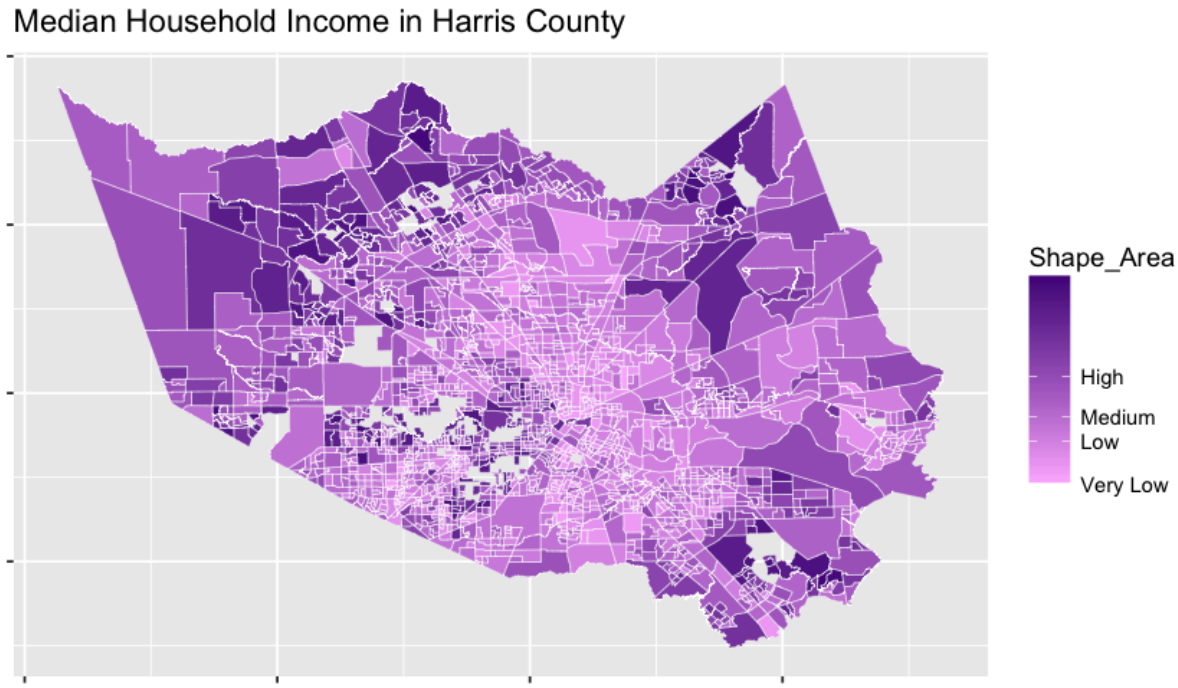
In [65]:
```
boxplot(censusBoundary.harris_clean@data$MedHHinc)
```



What happens if we remove the outliers and make the map again?

In [66]:

```
# convert a spatial object into data.frame
HarrisCty.tidy_rm_ot <- ggplot2::fortify(censusBoundary.harris_clean_rm_ol
, region="id")

HarrisCty.tidy_rm_ot_merge <- merge(HarrisCty.tidy_rm_ot, censusBoundary.h
arris_clean_rm_ol@data, by="id")

map_HarrisCty_rm_ot_merge <- ggplot(data=HarrisCty.tidy_rm_ot_merge, aes(l
ong,lat,group=group,fill=MedHHinc)) +
  geom_polygon() +
  geom_path(color = "white", size=0.1) +
  scale_fill_gradient(low = "plum1", high = "purple4",
                      breaks = quantile(censusBoundary.harris_clean@data$M
edHHinc),
                      labels=c("Very Low", "Low", "Medium", "High", "Very
 High")) +
  coord_equal() +
  theme(axis.title = element_blank(), axis.text = element_blank()) +
  labs(title = "Median Household Income in Harris County", fill = "Median
 Household Income")

map_HarrisCty_rm_ot_merge
```

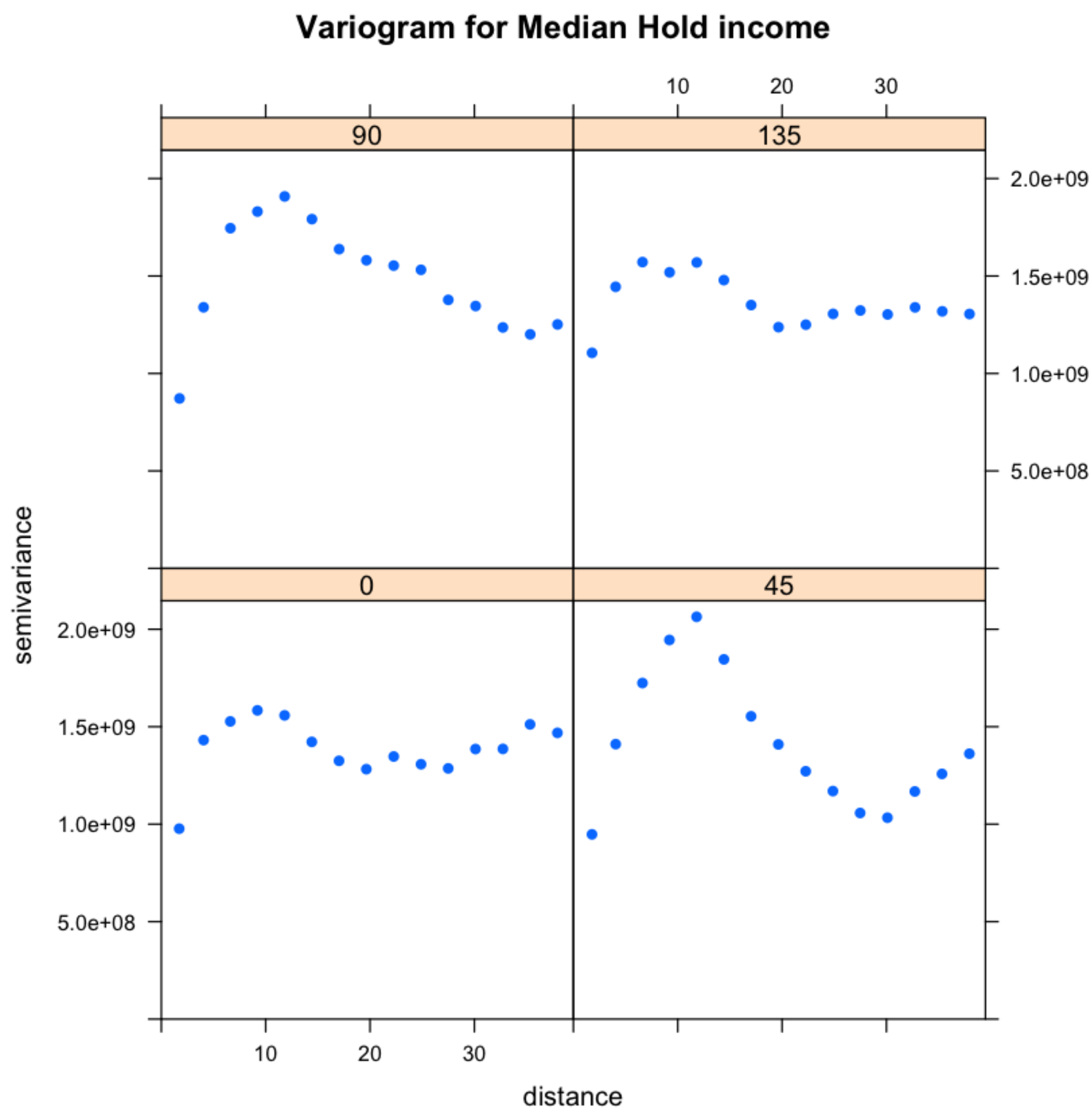


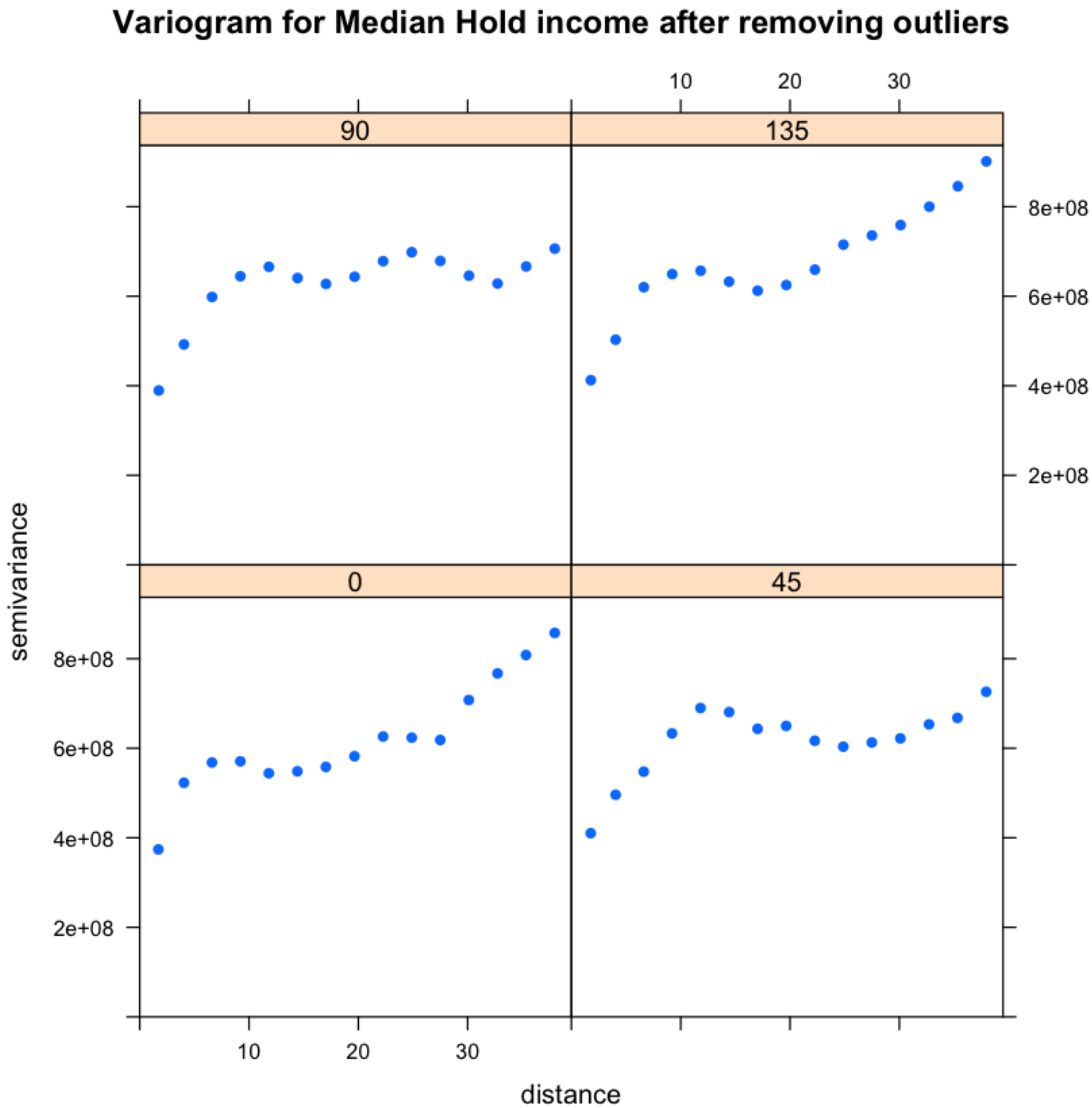
The map looks more colorful after removing outliers! Here, we are using the same breaks for the two maps. The "high" value becomes much higher in the second plot.

And very clearly, there are some spatial patterns in both the two maps!

Using Variogram to check spatial patterns

In [69]:
```
## variogram
harris_vgm <- gstat::variogram(MedHHinc~1, censusBoundary.harris_clean, al
pha = c(0, 45, 90, 135))
harris_vgm_rm_ol <- gstat::variogram(MedHHinc~1, censusBoundary.harris_cle
an_rm_ol, alpha = c(0, 45, 90, 135))

#census_grid <- sp::spsample(x=censusBoundary, bb=bbox_census, 10000, type
="regular")
#plot(MedHHinc_vgm_cloud, main = "Variogram Cloud for MedHHinc", pch = 16)

#Hisp_vgm <- gstat::variogram(Hisp~long+lat, censusBoundary.harris)
plot(harris_vgm, main = "Variogram for Median Hold income", pch = 16)
plot(harris_vgm_rm_ol, main = "Variogram for Median Hold income after remo
ving outliers", pch = 16)
```



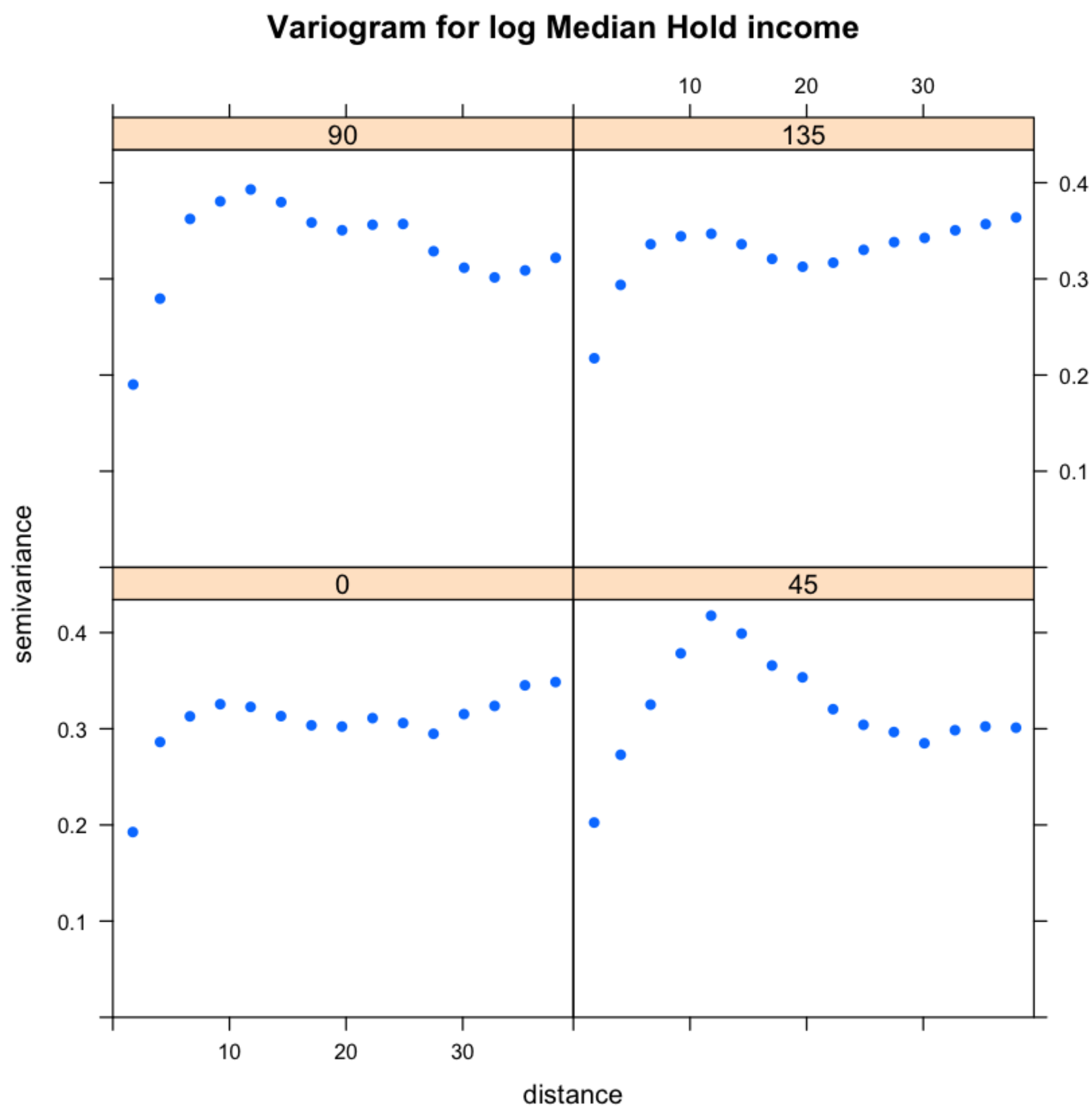


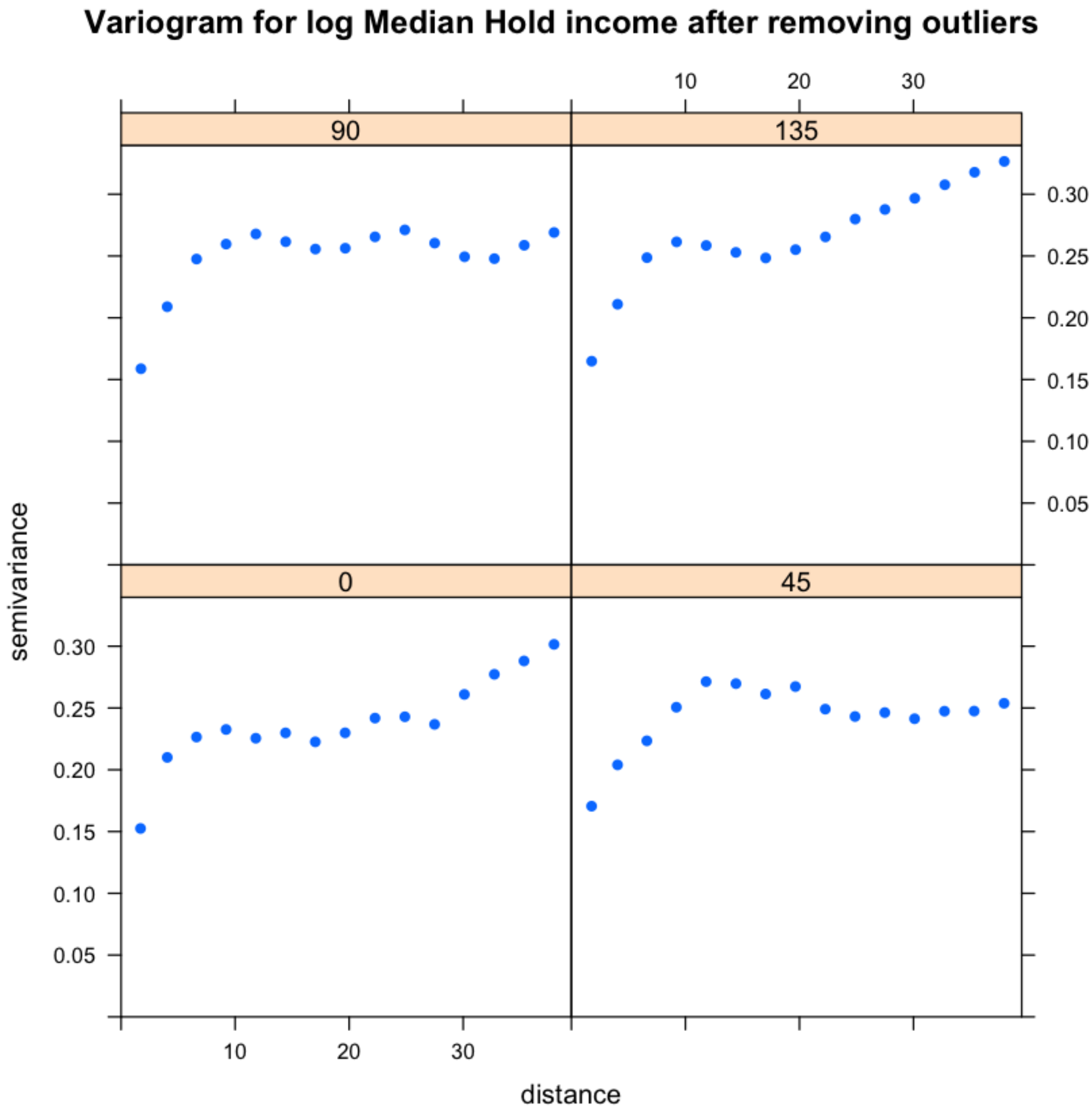
Checking for anisotropy, we change direction in plane (x,y) in positive (0, 45, 90, 135) degrees clockwise from positive y (North). Obviously, direction in plane (x,y) actually matters for variogram of Median Household Income.

As we can see in the Y-axis, the scale is very large. Would the variogram change rapidly if we change the scale?

In [71]:

```
## variogram
harris_vgm <- gstat::variogram(log(MedHHinc)~1, censusBoundary.harris_clea
n, alpha = c(0, 45, 90, 135))
harris_vgm_rm_ol <- gstat::variogram(log(MedHHinc)~1, censusBoundary.harri
s_clean_rm_ol, alpha = c(0, 45, 90, 135))

#census_grid <- sp::spsample(x=censusBoundary, bb=bbox_census, 10000, type
="regular")
#plot(MedHHinc_vgm_cloud, main = "Variogram Cloud for MedHHinc", pch = 16)

#Hisp_vgm <- gstat::variogram(Hisp~long+lat, censusBoundary.harris)
plot(harris_vgm, main = "Variogram for log Median Hold income", pch = 16)
plot(harris_vgm_rm_ol, main = "Variogram for log Median Hold income after
 removing outliers", pch = 16)
```





Changing the scale, the shapes do change a little bit. Based on these plots, after removing outliers, the spatial patterns are easiest to interpret with changing direction in plane (x,y) in positive 45 or 90 degrees clockwise from positive y (North).

Statistical tests for spatial dependence

Using Moran I test and Geary C test, we can test whether the observations are spatially independent or not.

H0: There is no spatial clustering of the values associated with the geographic features.

H1: There is spatial clustering of the values associated with the geographic features.

In [14]:
```
censusBoundary_nb <- spdep::poly2nb(censusBoundary.harris)
censusBoundary_listw <- spdep::nb2listw(censusBoundary_nb, style = "W", ze
ro.policy=T)

spdep::moran.test(censusBoundary.harris@data$MedHHinc,
           censusBoundary_listw,
           zero.policy = T)
spdep::geary.test(censusBoundary.harris@data$MedHHinc,
           censusBoundary_listw,
           zero.policy = T)
```

```
        Moran I test under randomisation

data:  censusBoundary.harris@data$MedHHinc
weights: censusBoundary_listw

Moran I statistic standard deviate = 41.376, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     0.5356437064     -0.0004909180      0.0001679005

        Geary C test under randomisation

data:  censusBoundary.harris@data$MedHHinc
weights: censusBoundary_listw

Geary C statistic standard deviate = 37.613, p-value < 2.2e-16
alternative hypothesis: Expectation greater than statistic
sample estimates:
Geary C statistic       Expectation          Variance
     0.4584276008      1.0000000000      0.0002073164
```

Both Moran I test and Geary C test show that there are strong evidences to show that there is spatial clustering of the values associated with the geographic features.

Modelling using Kriging

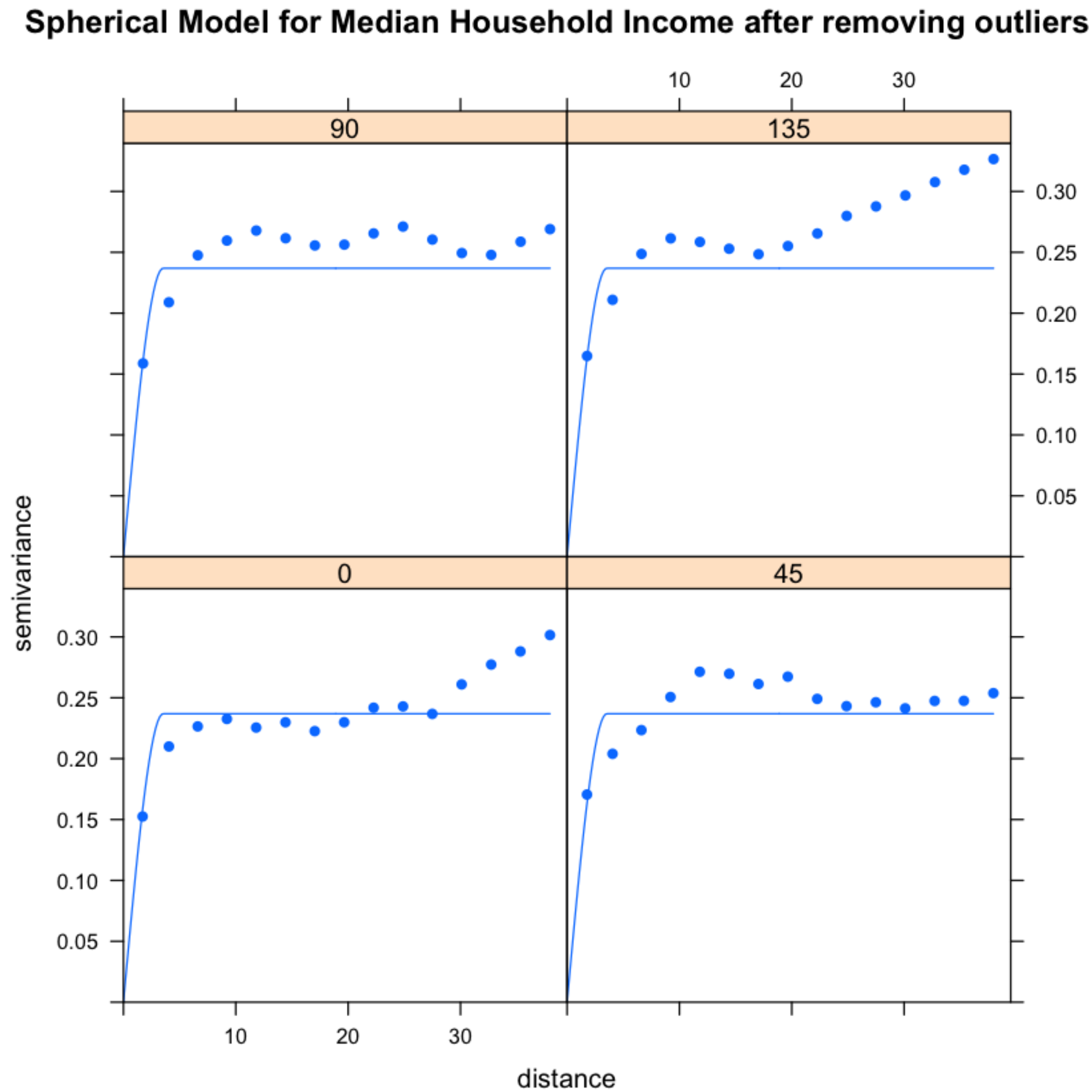
In [72]:
```
# using "grid" as new data
bbox_census <- sp::bbox(censusBoundary.harris_clean_rm_ol)
census_grid <- sp::spsample(x=censusBoundary.harris_clean_rm_ol,
                            bb=bbox_census, 10000, type="regular")
gridded(census_grid)     <- TRUE  # Create SpatialPixel object
fullgrid(census_grid)    <- TRUE  # Create SpatialGrid object
proj4string(census_grid) <- proj4string(censusBoundary.harris)
```

In [76]:

```
#spherical fit
mmhi_fit_sph <- gstat::fit.variogram(harris_vgm_rm_ol,
                                      model = gstat::vgm(model =  "Sph"))
print(mmhi_fit_sph)
plot(harris_vgm_rm_ol, mmhi_fit_sph, main = "Spherical Model for Median Ho
usehold Income after removing outliers", pch = 16)

#exponential fit
mmhi_vgm_exp <- gstat::fit.variogram(harris_vgm_rm_ol, model = gstat::vgm(
model =  "Exp"))
print(mmhi_vgm_exp)
plot(harris_vgm_rm_ol, mmhi_vgm_exp, main = "Exponential Model for Median
 Household Income after removing outliers", pch = 16)


## kriging

## spherical model

mmhi_krig_sph <- gstat::krige(MedHHinc~1,
                              censusBoundary.harris_clean_rm_ol,
                              census_grid,
                              model = mmhi_fit_sph)

## exponential model

mmhi_krig_exp <- gstat::krige(MedHHinc~1,
                              censusBoundary.harris_clean_rm_ol,
                              census_grid,
                              model = mmhi_vgm_exp)
```

```
  model     psill    range
1   Sph 0.2369033 3.537678
```

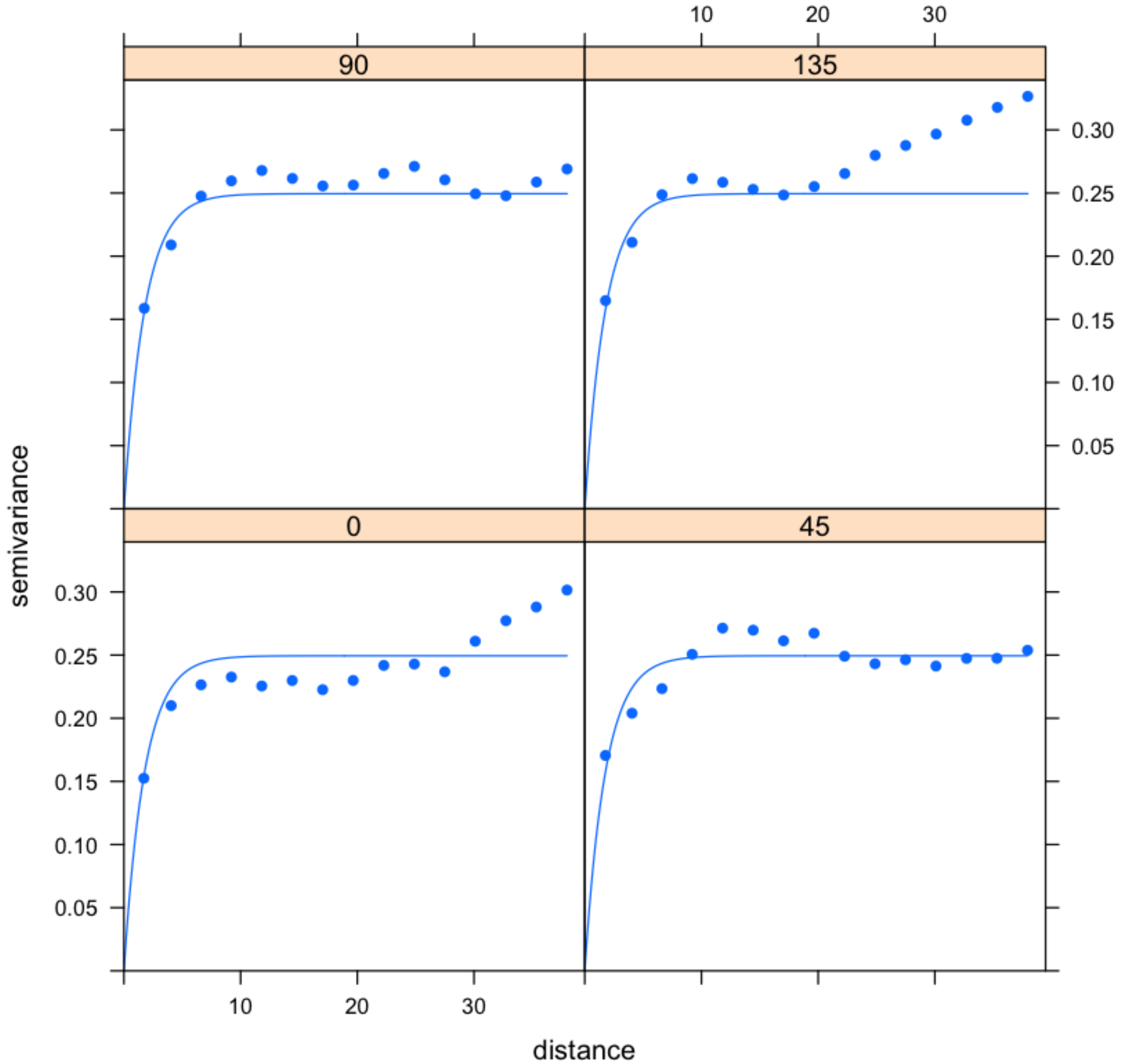
```
  model     psill    range
1   Exp 0.2494511 1.775872
```




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

'sph.cv <- gstat::krige.cv(MedHHinc~1, \n   locations = censusBoundary.harris, \n model = mmhi_fit_sph) ## cross validation\nexp.cv <- gstat::krige.cv(MedHHinc~1, \n locations = censusBoundary.harris, \n   model = mmhi_vgm_exp) ## cross validation\nmean(sph.cv$residual^2$)\nmean($exp.cv$residual^2)'

Exponential Model for Median Household Income after removing outliers



Using ordinary kriging, fitting model with changing direction in plane (x,y) in positive 45 or 90 degrees clockwise from positive y (North) seems to be the best.

Reference

American Community Survey (ACS) 2010. Urban Data Platform, Kinder Institute for Urban Research. https://www.kinderudp.org/#/datasetCatalog/8koe0a2ka4qb (https://www.kinderudp.org/#/datasetCatalog/8koe0a2ka4qb)

SoS Notebook: An Interactive Multi-Language Data Analysis Environment. Bo Peng, Gao Wang, Jun Ma, Man Chong Leong, Chris Wakefield, James Melott, Yulun Chiu, Di Du, and John N. Weinstein, Bioinformatics, May 2018. doi: https://doi.org/10.1093/bioinformatics/bty405 (https://doi.org/10.1093/bioinformatics/bty405)

Using R — Working with Geospatial Data (and ggplot2). Bethany Yollin http://mazamascience.com/WorkingWithData/?p=1494 (http://mazamascience.com/WorkingWithData/?p=1494)

How Spatial Autocorrelation: Moran's I (Spatial Statistics) works http://resources.esri.com/help/9.3/arcgisengine/java/gp_toolref/spatial_statistics_tools/how_spatial_autocorrelation_ (http://resources.esri.com/help/9.3/arcgisengine/java/gp_toolref/spatial_statistics_tools/how_spatial_autocorrelation

Notes and code example from STAT 551.