STAT 551

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Vignette 2 - Spatial data visualization with ggplot2 and Interpolation for polygon level data - of House Hold Income in Harris County

Goal

In Vignette 1, we found out that spatial patterns of Median Household income do exist in Houston. Can we fit statistical models based on these spatial patterns?

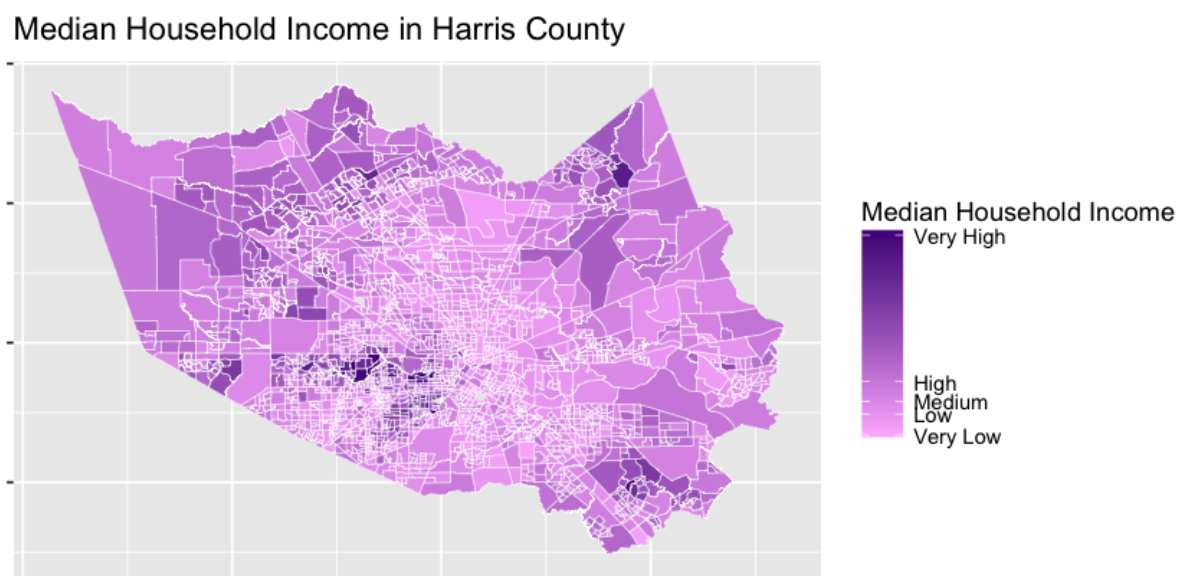
In this Vignette, we will see how to further visualize spatial data using ggplot2, and fit statistical models for prediction with polygon data.

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

In [8]:
```
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), ]

# 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), ]

# 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
```

```
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
```



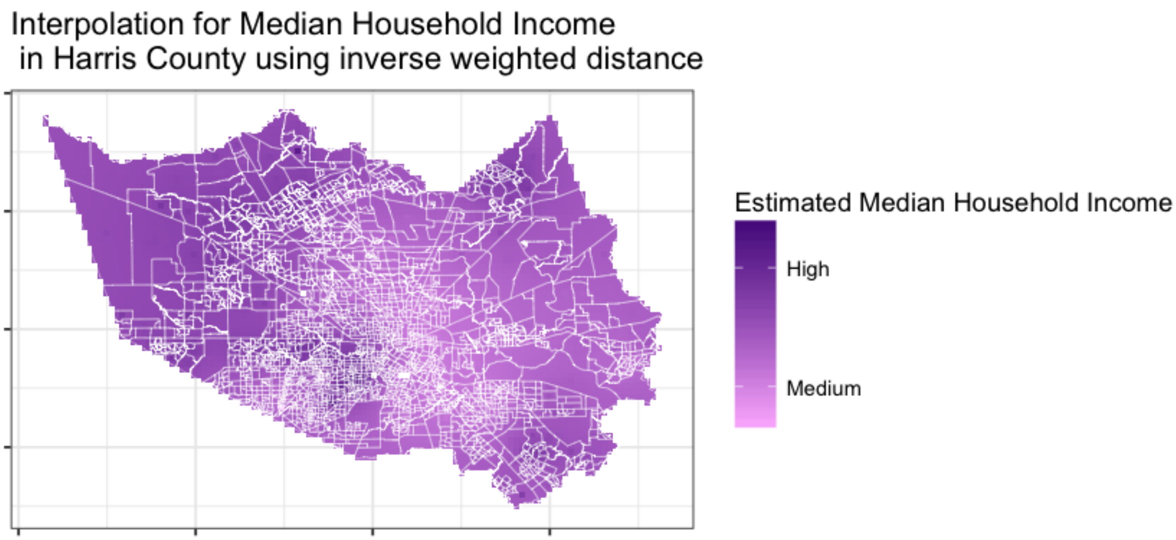
Recall from Vignette 1, there are some outliers. How would these outliers affect interpolation? Should we remove them for interpolation?

Interpolation for Median Household Income in Harris County using inverse weighted distance

Inverse weighted distance (IDW) should be one of the easiest method for interpolation. It is nothing special but to interpolate only based on distances of points.

In [9]:
```
grid <-spsample(censusBoundary.harris_clean, type = 'regular', n = 5000)

Result_num.idw <- gstat::idw((MedHHinc)~1,
                             location=censusBoundary.harris_clean,
                             #newdata=harris.grid,
                             newdata=grid,
                             idp=1)

idw.output = as.data.frame(Result_num.idw)

names(idw.output)[1:3] <- c("long", "lat", "prediction")

idw.output = as.data.frame(Result_num.idw)
idw_plot <- ggplot() +
  geom_tile(data = idw.output %>%
            rename(`Estimated Median Household Income`=var1.pred),
            aes(x = x1, y = x2, fill = `Estimated Median Household Income`
)) +
  #scale_fill_distiller(palette = "Spectral", direction = 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")) +
  theme_bw()  +
  coord_equal()

# 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")

new_plot <- idw_plot +
  geom_path(data=HarrisCty.tidy_merge, aes(long,lat,group=group),
            color = "white", size=0.1) +
  theme(axis.title = element_blank(), axis.text = element_blank()) +
  labs(title = "Interpolation for Median Household Income\n in Harris Coun
ty using inverse weighted distance")

new_plot
```

[inverse distance weighted interpolation]



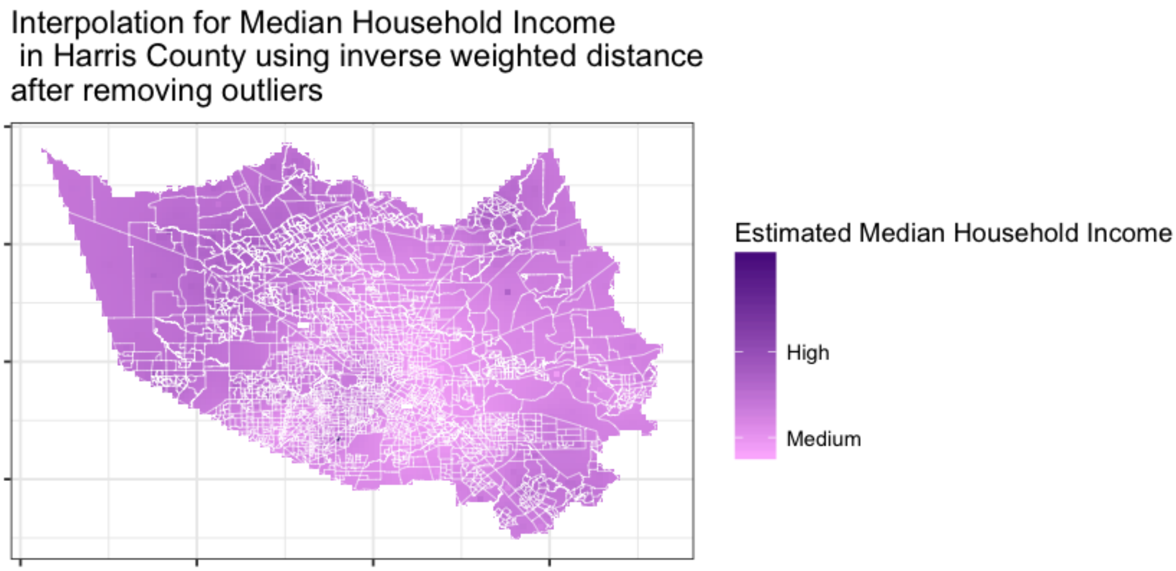
These outliers "pull" all the estimated values up. Using the same break with the actual values, none of the estimated values belong to the groups below "Low". Also, there are no estimated values get close to "very high".

All in all, smoothing without dealing with outliers is a very bad idea.

What if the outliers get excluded?

In [10]:
```
grid <-spsample(censusBoundary.harris_clean, type = 'regular', n = 5000)

Result_num.idw <- gstat::idw((MedHHinc)~1,
                             location=censusBoundary.harris_clean_rm_ol,
                             #newdata=harris.grid,
                             newdata=grid,
                             idp=1)

# grab output of IDW for plotting
idw.output = as.data.frame(Result_num.idw)  # output is defined as a data
 table
# set the names of the idw.output columns
# basic ggplot using geom_tile to display our interpolated grid within no
 map
idw_plot <- ggplot() +
  geom_tile(data = idw.output %>%
            rename(`Estimated Median Household Income`=var1.pred),
            aes(x = x1, y = x2, fill = `Estimated Median Household Income`
)) +
  #scale_fill_distiller(palette = "Spectral", direction = 1) +
  scale_fill_gradient(low = "plum1", high = "purple4",
                      breaks = quantile(censusBoundary.harris_clean_rm_ol@
data$MedHHinc),
                      labels=c("Very Low", "Low", "Medium", "High", "Very
 High")) +
  theme_bw()  +
  coord_equal()

# 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")

new_plot <- idw_plot +
  geom_path(data=HarrisCty.tidy_merge, aes(long,lat,group=group),
            color = "white", size=0.1) +
  theme(axis.title = element_blank(), axis.text = element_blank()) +
  labs(title = "Interpolation for Median Household Income\n in Harris Coun
ty using inverse weighted distance\nafter removing outliers")

new_plot
```

[inverse distance weighted interpolation]



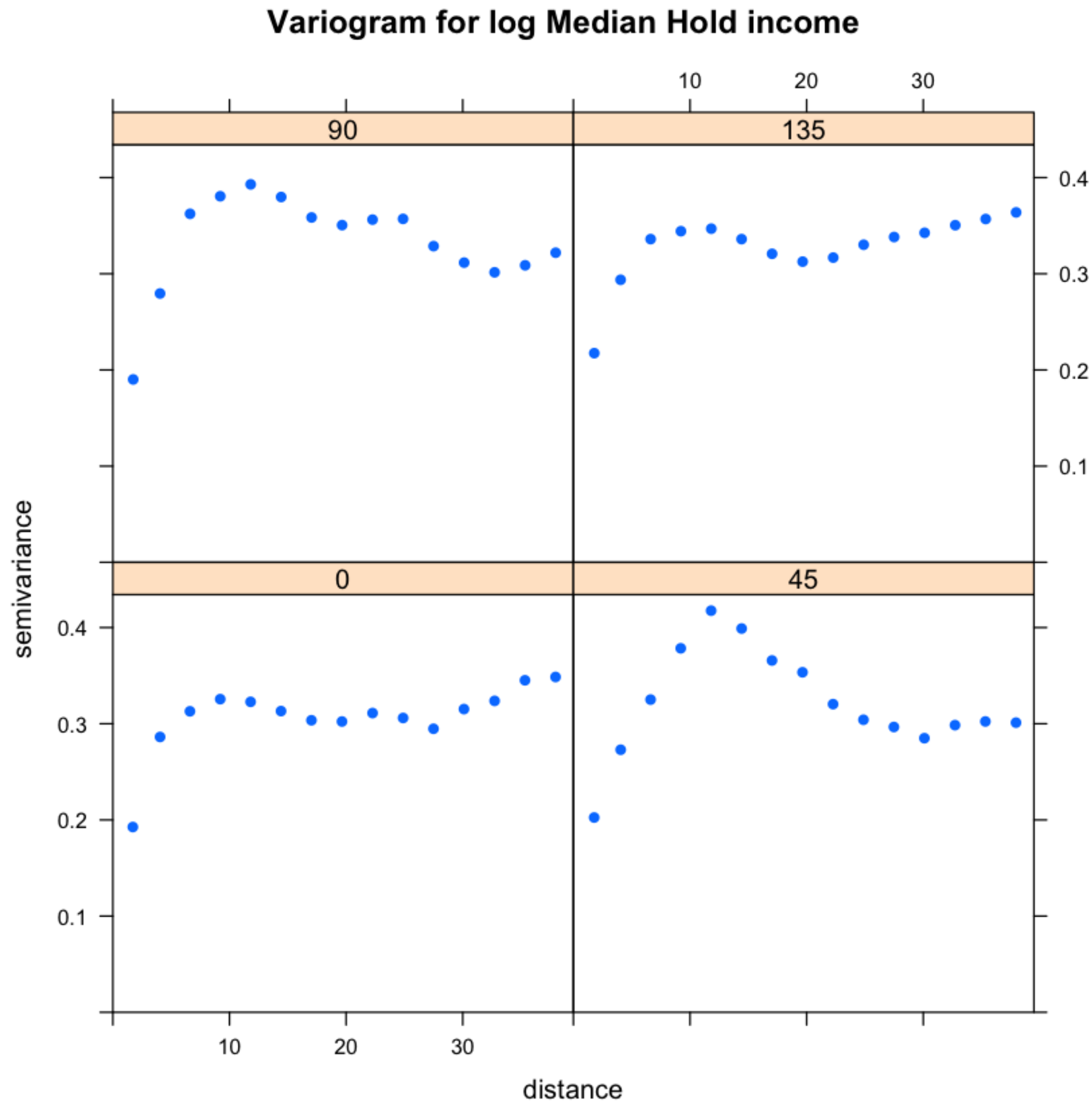
After removing outliers, the interpolation becomes much smoother. However, is it really better than including outliers?

This question is arguable. When the targets that we are interested in are those outliers or related to those outliers, including them might not be a bad idea. However, if we are more interested in the general picture, not specific patterns, then removing outliers will be a better choice.

Kriging

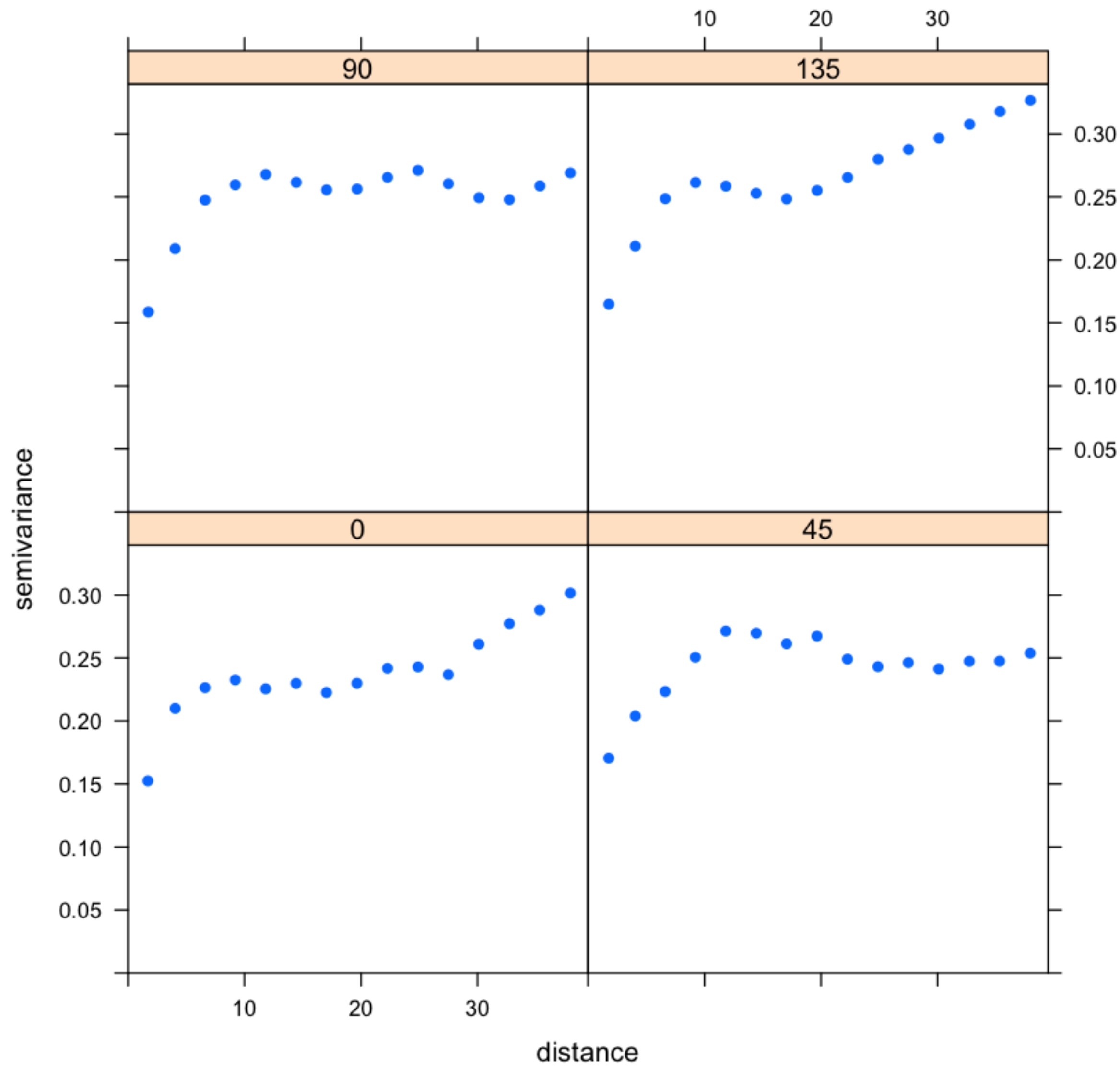
Recall from Vignette 1:

In [12]:
```
## variogram
harris_vgm <- gstat::variogram(log(MedHHinc)~1,
                               censusBoundary.harris_clean,
                               alpha = c(0, 45, 90, 135))
harris_vgm_rm_ol <- gstat::variogram(log(MedHHinc)~1,
                                     censusBoundary.harris_clean_rm_ol,
                                     alpha = c(0, 45, 90, 135))

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)

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 Household Income after removing ou
tliers",
     pch = 16)

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)
```



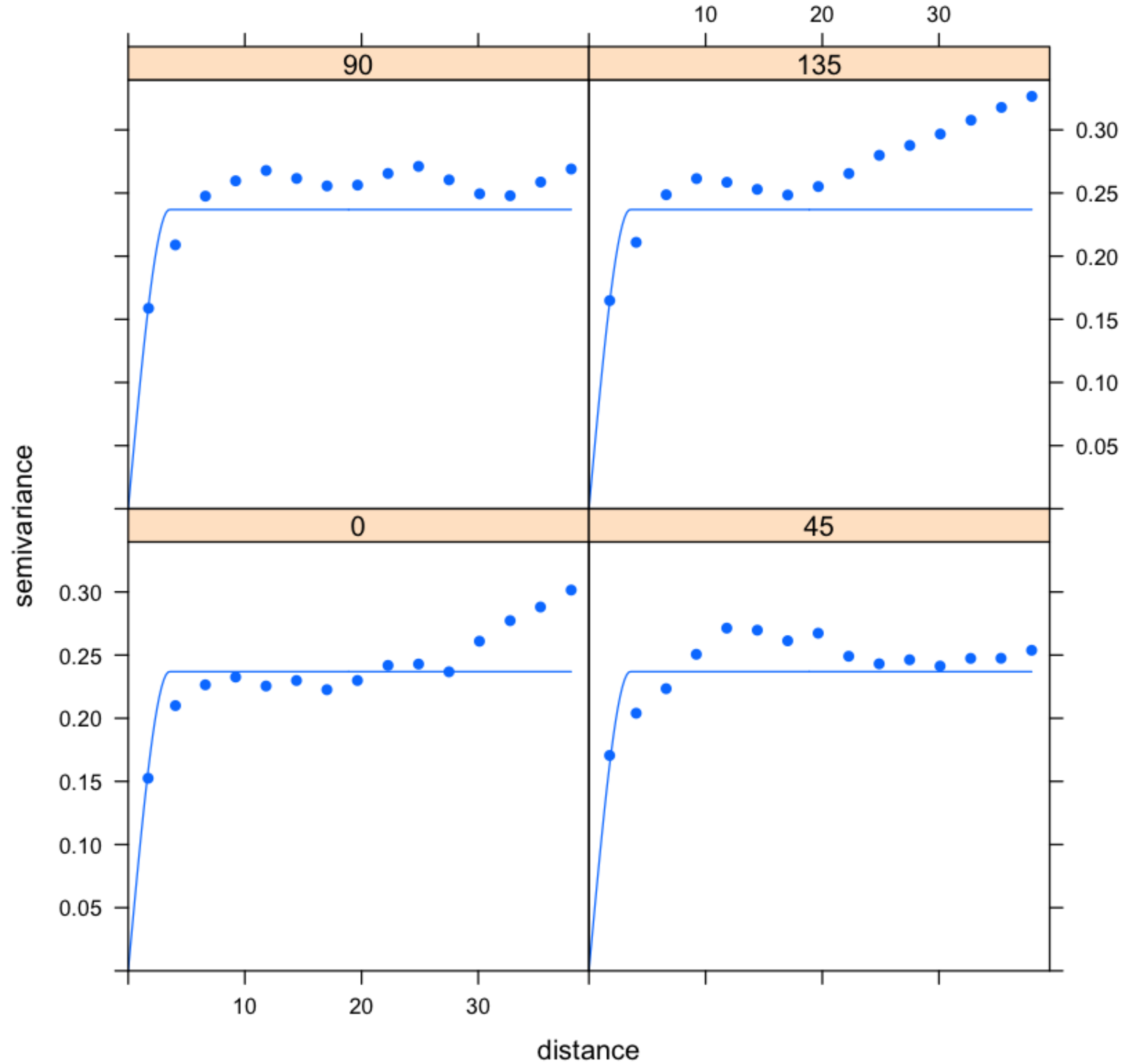

```
  model     psill    range
1   Sph 0.2369033 3.537678
```

Variogram for log Median Hold income after removing outliers

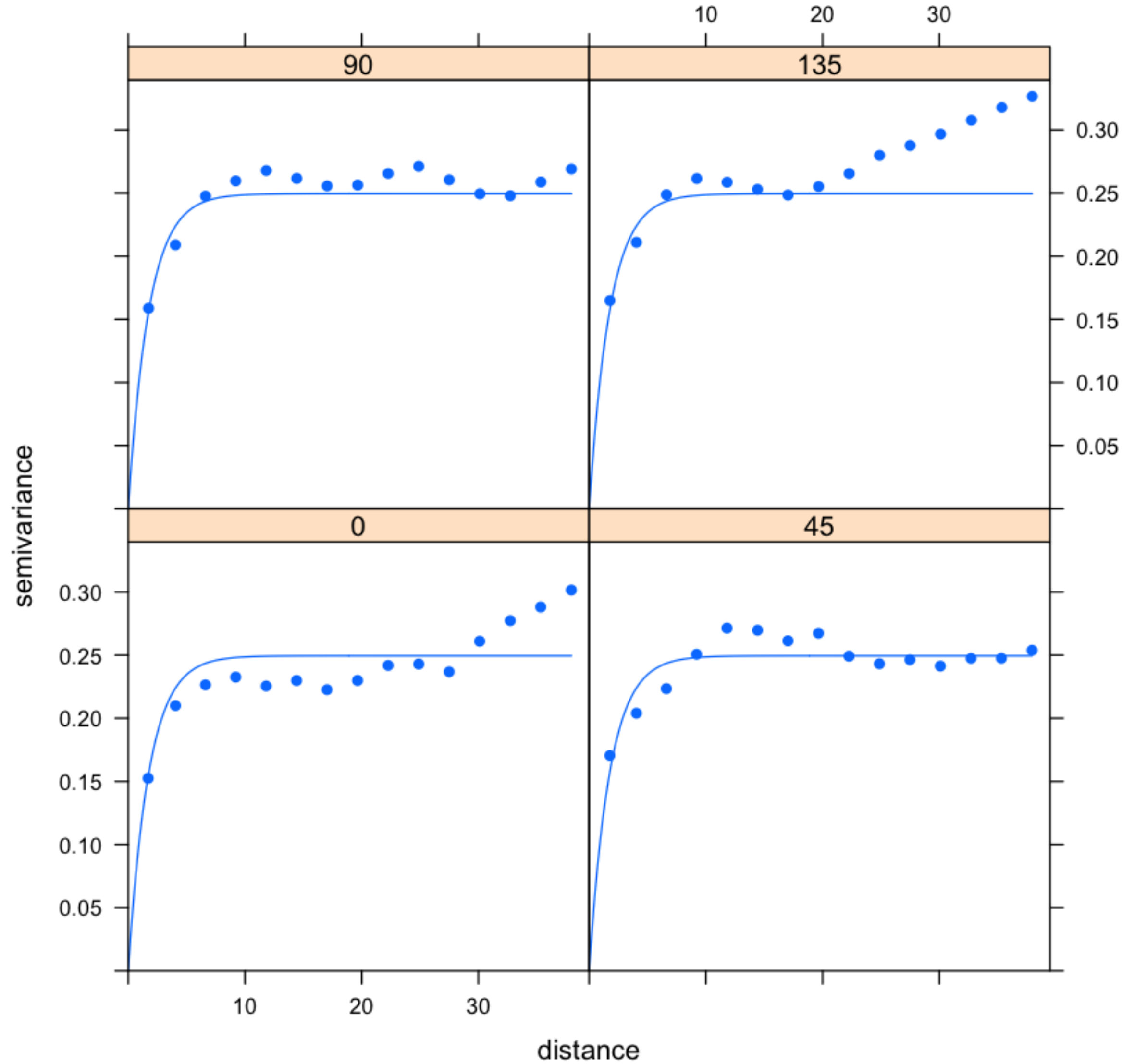



```
  model     psill    range
1   Exp 0.2494511 1.775872
```

Spherical Model for Median Household Income after removing outliers



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. (Both Spherical Model and Exponential Model)

Based on these conclusion, we can use the conclusion we got last time for interpolation.

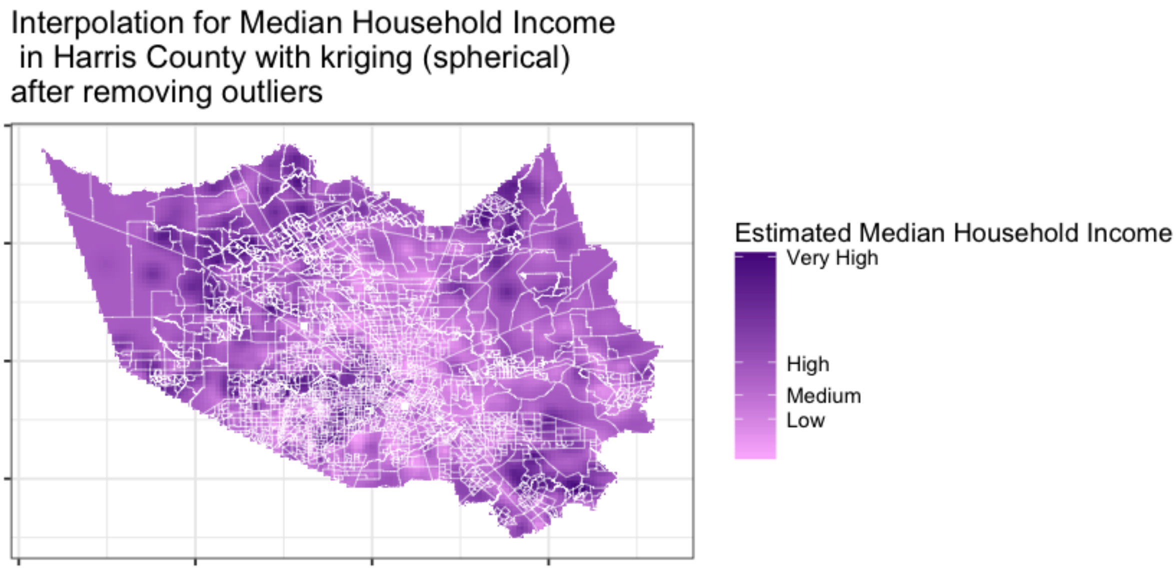
For Vignette purpose, only model with changing direction in plane (x,y) in positive 45 degrees clockwise from positive y (North) will be used.

Spherical Model

In [13]:
```
harris_vgm <- gstat::variogram(log(MedHHinc)~1,
                               censusBoundary.harris_clean,
                               alpha = 45)
harris_vgm_rm_ol <- gstat::variogram(log(MedHHinc)~1,
                                     censusBoundary.harris_clean_rm_ol,
                                     alpha = 45)
mmhi_fit_sph_rm_ol <- gstat::fit.variogram(harris_vgm_rm_ol,
                                      model = gstat::vgm(model =  "Sph"))
mmhi_fit_sph <- gstat::fit.variogram(harris_vgm,
                                      model = gstat::vgm(model =  "Sph"))

census_grid <- sp::spsample(x=censusBoundary.harris_clean,
                            10000, type="regular")
gridded(census_grid) <- TRUE
proj4string(census_grid) <- proj4string(censusBoundary.harris)

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

```
[using ordinary kriging]
```

In [14]:
```
krig_sph.output <- as.data.frame(mmhi_krig_sph)

krig_sph_plot <- ggplot() +
  geom_tile(data = krig_sph.output %>%
            rename(`Estimated Median Household Income`=var1.pred),
            aes(x = x1, y = x2, fill = `Estimated Median Household Income`
)) +
  #scale_fill_distiller(palette = "Spectral", direction = 1) +
  scale_fill_gradient(low = "plum1", high = "purple4",
                      breaks = quantile(censusBoundary.harris_clean_rm_ol@
data$MedHHinc),
                      labels=c("Very Low", "Low", "Medium", "High", "Very
 High")) +
  theme_bw()  +
  coord_equal()

HarrisCty.tidy <- ggplot2::fortify(censusBoundary.harris_clean, region="i
d")

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

new_plot <- krig_sph_plot +
  geom_path(data=HarrisCty.tidy_merge,
            aes(long,lat,group=group),
            color = "white", size=0.1) +
  theme(axis.title = element_blank(),
        axis.text = element_blank()) +
  labs(title = "Interpolation for Median Household Income\n in Harris Coun
ty with kriging (spherical)\nafter removing outliers")

new_plot
```



Looks far better than IDW!

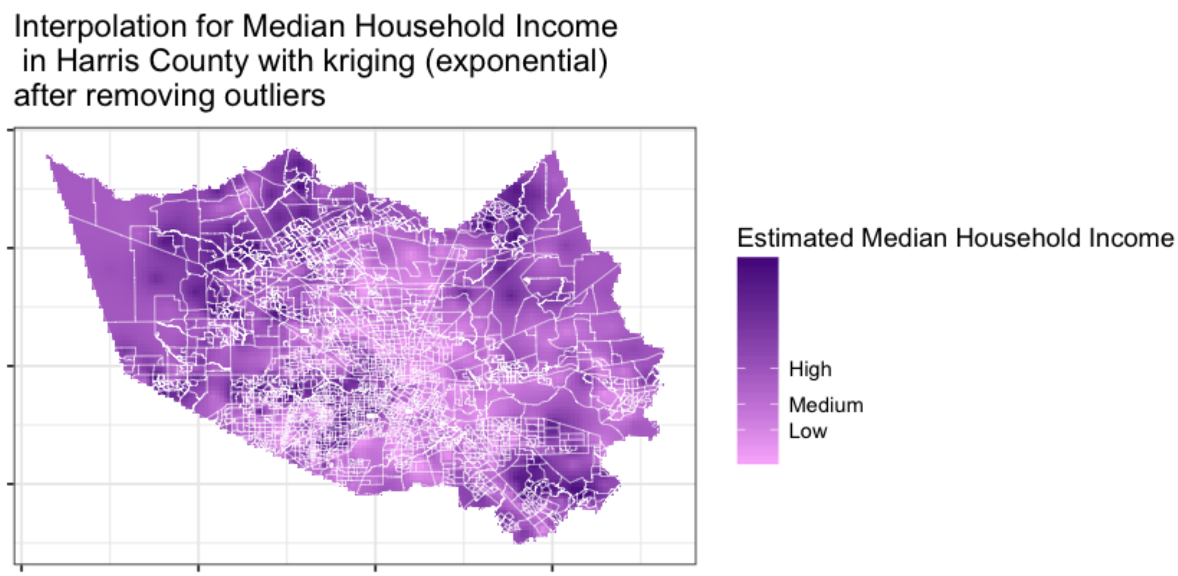
Exponential Model

In [15]:

```
harris_vgm <- gstat::variogram(log(MedHHinc)~1,
                               censusBoundary.harris_clean,
                               alpha = 45)
harris_vgm_rm_ol <- gstat::variogram(log(MedHHinc)~1,
                                     censusBoundary.harris_clean_rm_ol,
                                     alpha = 45)
mmhi_fit_exp_rm_ol <- gstat::fit.variogram(harris_vgm_rm_ol,
                                      model = gstat::vgm(model =  "Exp"))
mmhi_fit_exp <- gstat::fit.variogram(harris_vgm,
                                      model = gstat::vgm(model =  "Exp"))

# using "grid" as new data
census_grid <- sp::spsample(x=censusBoundary.harris_clean,
                            10000, type="regular")
gridded(census_grid) <- TRUE
proj4string(census_grid) <- proj4string(censusBoundary.harris)

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

```
[using ordinary kriging]
```

In [16]:
```
krig_exp.output <- as.data.frame(mmhi_krig_exp)
krig_exp_plot <- ggplot() +
  geom_tile(data = krig_exp.output %>%
            rename(`Estimated Median Household Income`=var1.pred),
            aes(x = x1, y = x2, fill = `Estimated Median Household Income`
)) +
  #scale_fill_distiller(palette = "Spectral", direction = 1) +
  scale_fill_gradient(low = "plum1", high = "purple4",
                      breaks = quantile(censusBoundary.harris_clean_rm_ol@
data$MedHHinc),
                      labels=c("Very Low", "Low", "Medium", "High", "Very
 High")) +
  theme_bw()  +
  coord_equal()

HarrisCty.tidy <- ggplot2::fortify(censusBoundary.harris_clean, region="i
d")

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

new_plot <- krig_exp_plot +
  geom_path(data=HarrisCty.tidy_merge, aes(long,lat,group=group),
            color = "white", size=0.1) +
  theme(axis.title = element_blank(), axis.text = element_blank()) +
  labs(title = "Interpolation for Median Household Income\n in Harris Coun
ty with kriging (exponential)\nafter removing outliers")

new_plot
```


Interpolation for Median Household Income
in Harris County with kriging (exponential)
after removing outliers
Estimated Median Household Income
High
Medium
Low

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)

Notes and code example from STAT 551.

Introduction to Kriging in R. Nabil A. https://rpubs.com/nabilabd/118172 (https://rpubs.com/nabilabd/118172)

Practical 11: Interpolating Point Data in R. https://www.cdrc.ac.uk/wp-content/uploads/2016/11/Practical_11.html (https://www.cdrc.ac.uk/wp-content/uploads/2016/11/Practical_11.html)

https://www.stat.berkeley.edu/~arturof/Teaching/STAT248/lab10_part2.html (https://www.stat.berkeley.edu/~arturof/Teaching/STAT248/lab10_part2.html)

Intro to spatial data in R - Open and plot raster and vector data with base plot. Leah A. Wasser https://nceas.github.io/oss-lessons/spatial-data-gis-law/4-tues-spatial-analysis-in-r.html (https://nceas.github.io/oss-lessons/spatial-data-gis-law/4-tues-spatial-analysis-in-r.html)