Predicting Price for Airbnb Listings - Using a Geostatistical Approach

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```
library(doParallel)
```

```
Loading required package: foreach
```

```
Loading required package: iterators
```

```
Loading required package: parallel
```

```
ncores <- detectCores()
clus <- makeCluster(ncores - 1)
registerDoParallel(clus)
```

All the data used in this report is from the 14 December 2024 report of Airbnb data from: https://insideairbnb.com/get-the-data/

```
set.seed(0)

austin_listings_orig <- read_csv("/home/narenprax/Documents/GitHub/STATS-C173-273/Final Proj
```

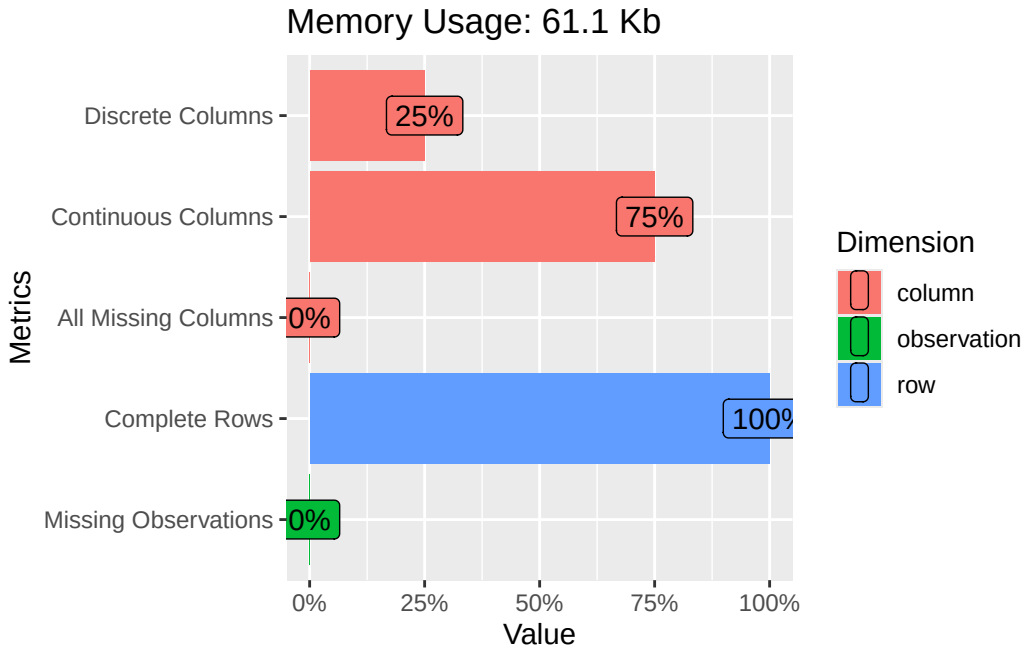
```
Rows: 15500 Columns: 75
-- Column specification --------------------------------------------------------
Delimiter: ","
chr  (23): listing_url, source, name, description, neighborhood_overview, pi...
dbl  (39): id, scrape_id, host_id, host_listings_count, host_total_listings_...
lgl   (8): host_is_superhost, host_has_profile_pic, host_identity_verified, ...
date  (5): last_scraped, host_since, calendar_last_scraped, first_review, la...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
austin_listings <- austin_listings_orig %>%
  select(c(longitude, latitude, property_type, room_type, bathrooms, bedrooms, beds, price)) %>%
  distinct(longitude, latitude, .keep_all = TRUE) %>%
  drop_na() %>%
  sample_n(1000) %>%
  mutate_if(is.character, as.factor)
austin_listings$price <- as.numeric(gsub("[^0-9\\.]", "", austin_listings$price))
```

Data Exploration and non-spatial analysis

Data overview

```r
library(DataExplorer)
plot_intro(austin_listings)
```

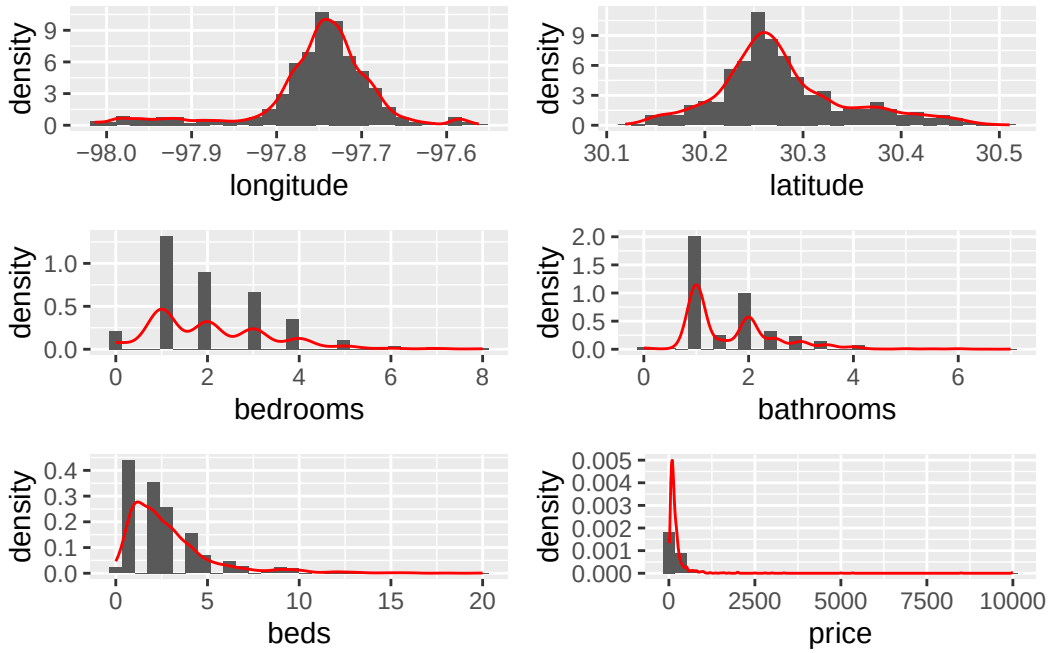



```r
kable(summary(austin_listings))
```

	longitude	latitude	property_type	room_type	bathrooms	bedrooms	beds	price
	Min. :-98.01	Min. :30.12	Entire home :430	Entire home/apt:861	Min. :0.000	Min. :0.000	Min. : 0.000	Min. : 18.0
	1st Qu.:-97.77	1st Qu.:30.24	Entire rental unit :185	Hotel room : 1	1st Qu.:1.000	1st Qu.:1.000	1st Qu.: 1.000	1st Qu.: 84.0
	Median :-97.74	Median :30.27	Private room in home: 94	Private room :135	Median :1.500	Median :2.000	Median : 2.000	Median : 133.0
	Mean :-97.75	Mean :30.28	Entire condo : 73	Shared room : 3	Mean :1.698	Mean :2.079	Mean : 2.897	Mean : 256.9
	3rd Qu.:-97.72	3rd Qu.:30.31	Entire guesthouse : 62	NA	3rd Qu.:2.000	3rd Qu.:3.000	3rd Qu.: 4.000	3rd Qu.: 225.0
	Max. :-97.56	Max. :30.51	Entire guest suite : 22	NA	Max. :7.000	Max. :8.000	Max. :20.000	Max. :10000.0
	NA	NA	(Other) :134	NA	NA	NA	NA	NA

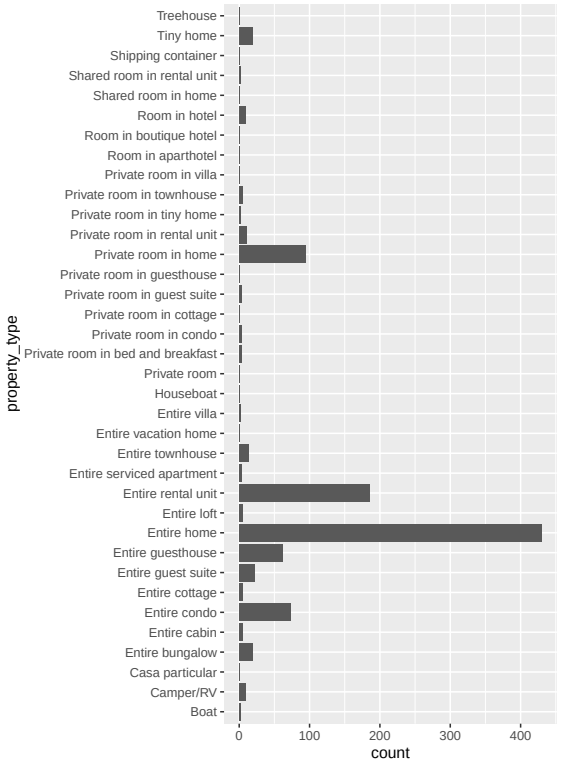
Numerical data exploration

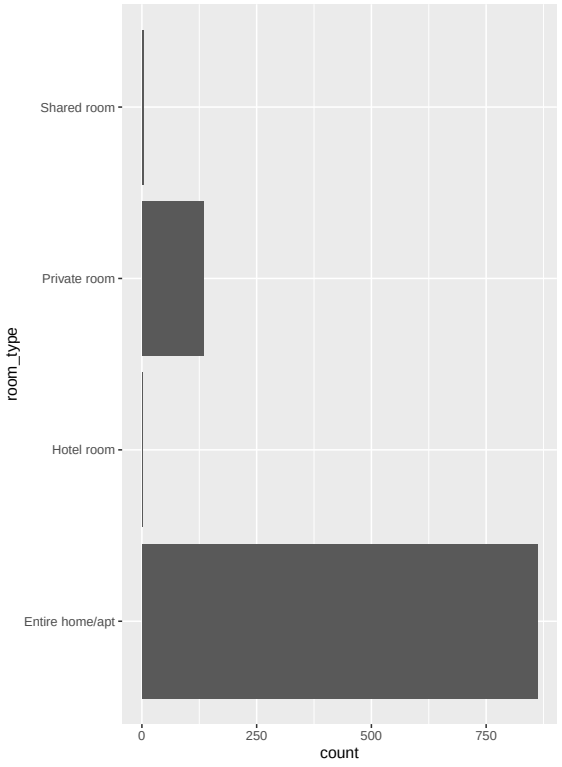
```
long_hist <- austin_listings %>% ggplot(aes(x = longitude)) +
  geom_histogram(aes(y = ..density..)) +
  geom_density(col = "red")
lat_hist <- austin_listings %>% ggplot(aes(x = latitude)) +
  geom_histogram(aes(y = ..density..)) +
  geom_density(col = "red")
bed_hist <- austin_listings %>% ggplot(aes(x = bedrooms)) +
  geom_histogram(aes(y = ..density..)) +
  geom_density(col = "red")
bath_hist <- austin_listings %>% ggplot(aes(x = bathrooms)) +
  geom_histogram(aes(y = ..density..)) +
  geom_density(col = "red")
beds_hist <- austin_listings %>% ggplot(aes(x = beds)) +
  geom_histogram(aes(y = ..density..)) +
  geom_density(col = "red")
price_hist <- austin_listings %>% ggplot(aes(x = price)) +
  geom_histogram(aes(y = ..density..)) +
  geom_density(col = "red")

grid.arrange(long_hist, lat_hist, bed_hist, bath_hist, beds_hist, price_hist, nrow = 3)
```



Categorical data exploration

```
bar_prop <- austin_listings %>% ggplot(aes(x = property_type)) +
  geom_bar() +
  coord_flip()
bar_room <- austin_listings %>% ggplot(aes(x = room_type)) +
  geom_bar() +
  coord_flip()
grid.arrange(bar_prop, bar_room)
```

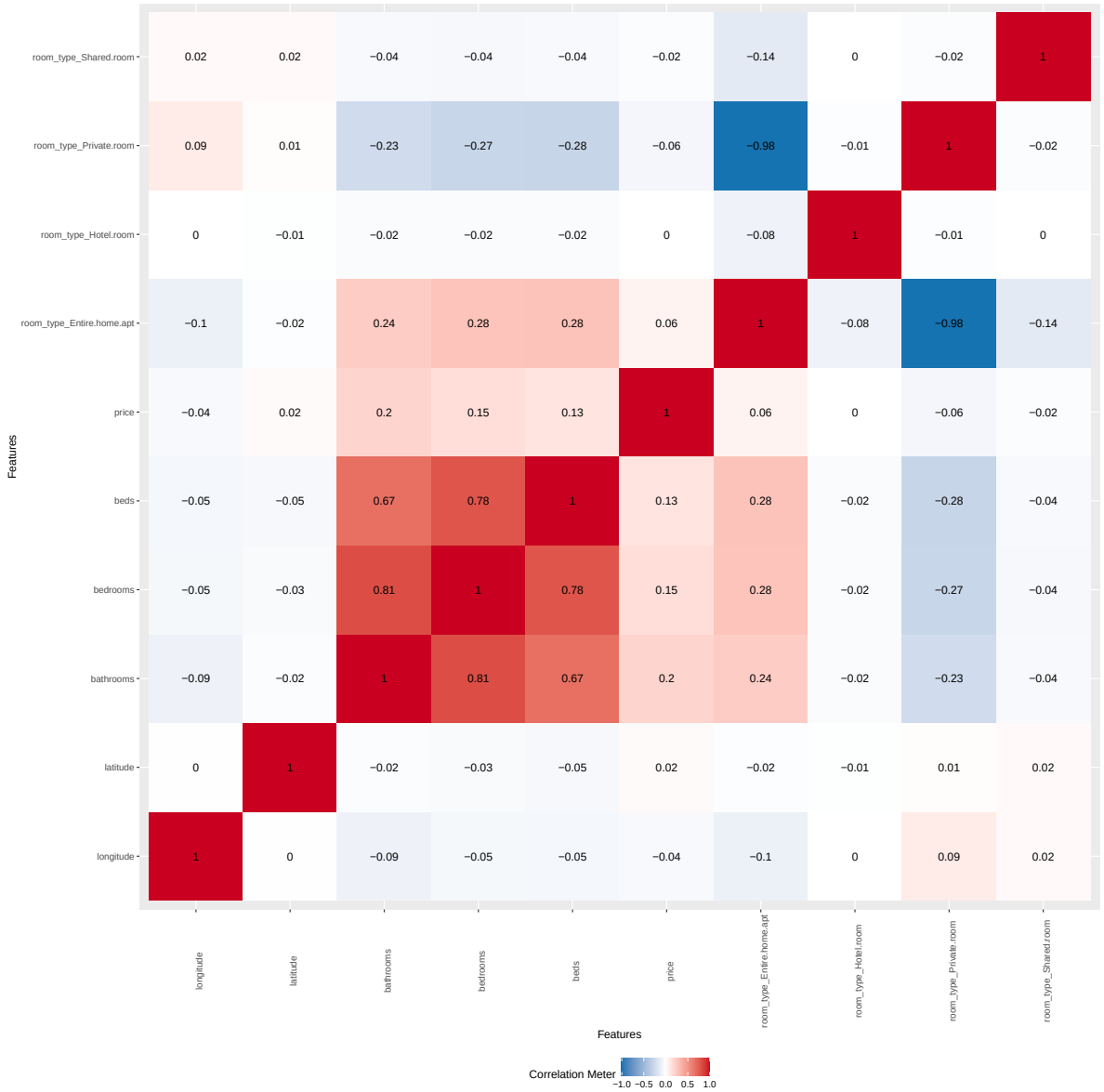

property_type
Treehouse
Tiny home
Shipping container
Shared room in rental unit
Shared room in home
Room in hotel
Room in boutique hotel
Room in aparthotel
Private room in villa
Private room in townhouse
Private room in tiny home
Private room in rental unit
Private room in home
Private room in guesthouse
Private room in guest suite
Private room in cottage
Private room in condo
Private room in bed and breakfast
Private room
Houseboat
Entire villa
Entire vacation home
Entire townhouse
Entire serviced apartment
Entire rental unit
Entire loft
Entire home
Entire guesthouse
Entire guest suite
Entire cottage
Entire condo
Entire cabin
Entire bungalow
Casa particular
Camper/RV
Boat
0
100
200
300
400
count


room_type
Shared room
Private room
Hotel room
Entire home/apt
0
250
500
750
count

Variable relationship exploration

```
plot_correlation(austin_listings)
```

```
1 features with more than 20 categories ignored!
property_type: 36 categories
```



We definitely have some correlation between different predictors.

Non-spatial analysis - LASSO regression for variable selection

```
library(glmnet)
```

```
Loading required package: Matrix
```

```

Attaching package: 'Matrix'
```

```
The following objects are masked from 'package:tidyr':

    expand, pack, unpack
```

```
Loaded glmnet 4.1-8
```

```
set.seed(0)

pred <- austin_listings %>% select(-price)
X <- data.matrix(pred)
y <- austin_listings$price

cv.model <- cv.glmnet(X, y, alpha = 1)
lam <- cv.model$lambda.min

best_mod <- glmnet(X, y, alpha = 1, lambda = lam)
coef(best_mod)
```

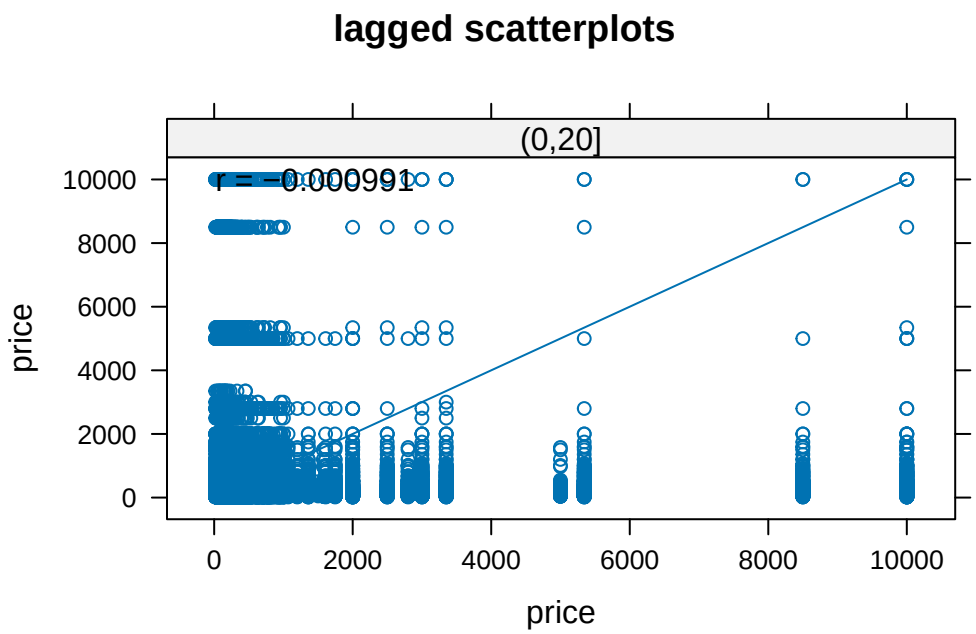
```
8 x 1 sparse Matrix of class "dgCMatrix"
                     s0
(Intercept)    46.0619
longitude       .
latitude        .
property_type   .
room_type       .
bathrooms     124.2221
bedrooms        .
beds            .
```

Based on the LASSO method of variable selection, only the variable bathrooms is a significant predictor for the price of a individual listing.

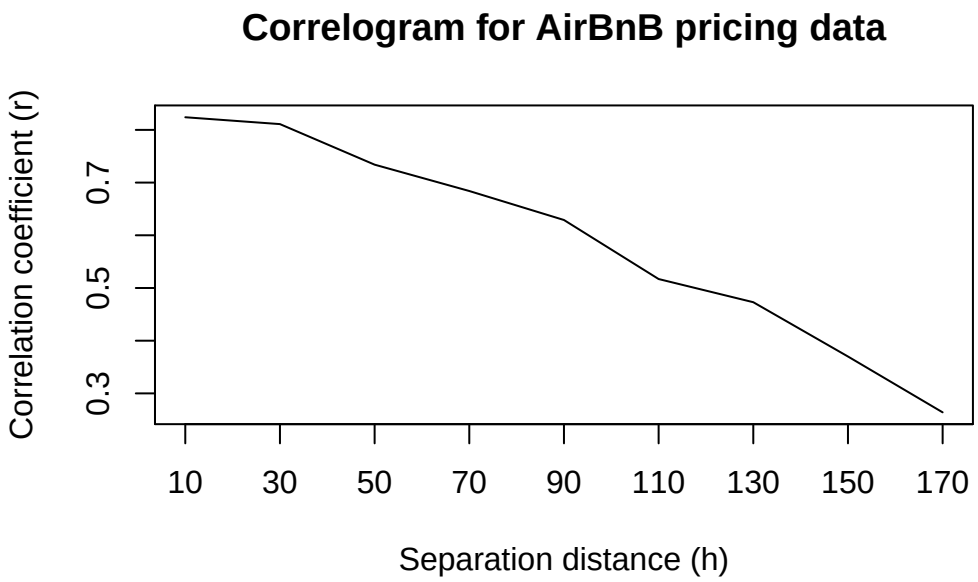
Geospatial Analysis

h-scatterplots and correlogram

```
library(sp)
library(gstat)

sp_listings <- austin_listings

coordinates(sp_listings) <- ~ longitude + latitude

qq <- hscat(price ~ 1, sp_listings, c(0, 20, 40, 60, 80, 100, 120, 140, 160, 180))

plot(qq, main = "h-scatterplots")
```




```
plot(c(10, 30, 50, 70, 90, 110, 130, 150, 170), c(0.824, 0.811, 0.734, 0.684, 0.629, 0.517, 0

axis(1, at = seq(10, 240, by = 20), labels = seq(10, 240, by = 20))

axis(2, at = seq(0, 1, by = 0.1), labels = seq(0, 1, by = 0.1))
```

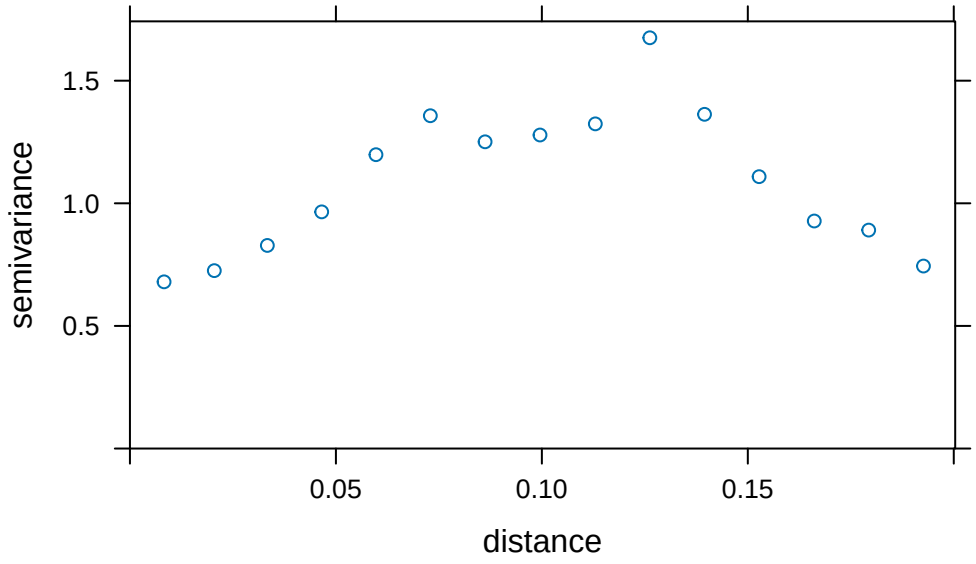


Variograms

Sample variogram

Scaling done for variogram ease later on.

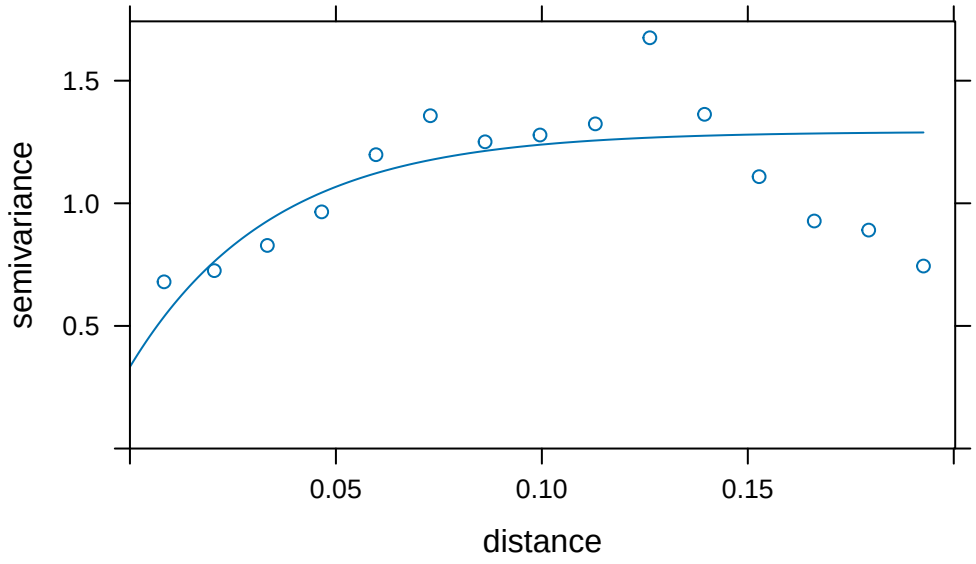
```
g <- gstat(id = "scaled price", formula = scale(price) ~ 1, locations = ~ longitude + latitu
samp <- variogram(g)
plot(samp)
```



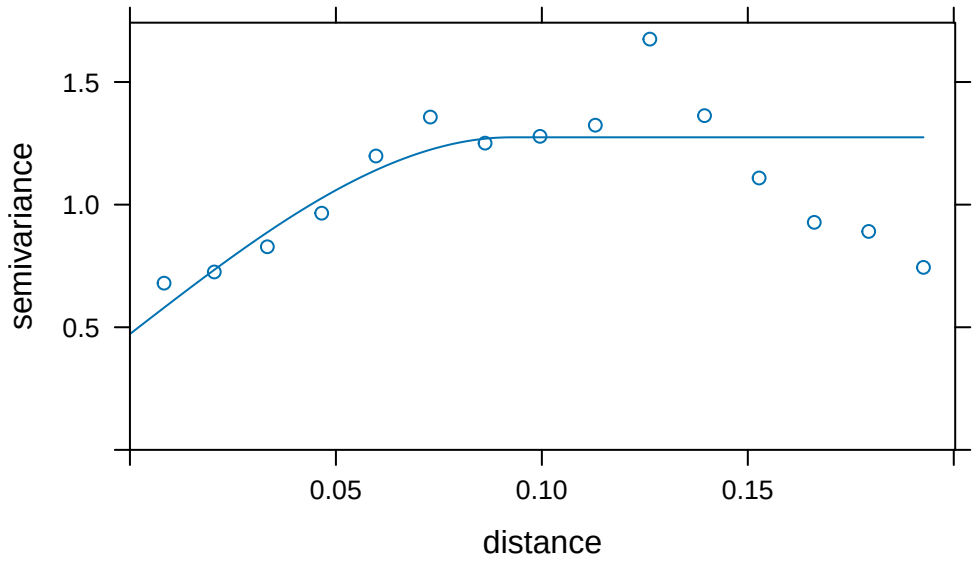
Different covariance function fits (using Cressie's weights)

```
exp_fit <- fit.variogram(samp, vgm(1.2, "Exp", 0.7, 0.3), fit.method = 2)
sph_fit <- fit.variogram(samp, vgm(1.2, "Sph", 0.7, 0.3), fit.method = 2)
```

```
plot(samp, exp_fit)
```




```
plot(samp, sph_fit)
```



Visually it is hard to choose the best covariance function. Instead, we will minimize PRESS.

Cross validation

```
sl <- sample(1:1000, 700)

train <- austin_listings[sl, ]
test <- austin_listings[-sl, ]
```

```
cvalid <- krige(id = "scaledprice", scale(price) ~ 1, locations = ~ longitude + latitude, mo
```

```
[using ordinary kriging]
```

```
difference <- scale(test$price) - cvalid$scaledprice.pred
summary(difference)
```

```
       V1
 Min.   :-2.88004
 1st Qu.:-0.20605
 Median :-0.10193
 Mean   : 0.01401
 3rd Qu.: 0.03235
 Max.   :13.60095
```

```
press1 <- sum(difference^2)
press1
```

```
[1] 314.8996
```

```
cvalid <- krige(id = "scaledprice", scale(price) ~ 1, locations = ~ longitude + latitude, mo
```

```
[using ordinary kriging]
```

```
difference <- scale(test$price) - cvalid$scaledprice.pred
summary(difference)
```

```
       V1
 Min.   :-1.941282
 1st Qu.:-0.220706
```

```
 Median :-0.125659
 Mean   : 0.005639
 3rd Qu.: 0.000283
 Max.   :13.555199
```

```
press2 <- sum(difference^2)
press2
```

```
[1] 304.6792
```

We see here that the spherical covariance model minimizes PRESS so we continue onward with this covariance function.

Kriging

We know there is one related variable, bathrooms, that has the most correlation with price. Let's investigate whether cokriging would be the best approach to price prediction.

Ordinary kriging

```
x.range <- as.integer(range(austin_listings[, 1]))
y.range <- as.integer(range(austin_listings[, 2]))
grd <- expand.grid(
  longitude = seq(from = x.range[1], to = x.range[2], by = 0.001),
  latitude = seq(from = y.range[1], to = y.range[2], by = 0.001)
)
```

```
pred <- krige.cv(formula = scale(price) ~ 1, data = austin_listings, locations = ~ longitude
```

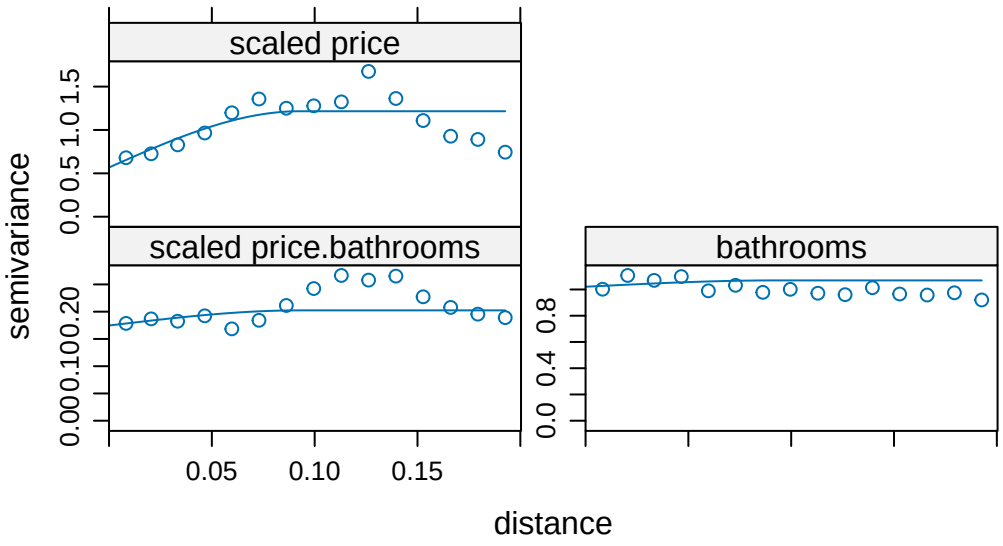
```
mean(pred$residual)
```

```
[1] 0.01774772
```

Ordinary Co-kriging

Adding the covariate and looking at the variogram plots:

```
all <- gstat(g, id = "bathrooms", formula = scale(bathrooms) ~ 1, locations = ~ longitude + l

var_all <- variogram(all)
all_fit <- fit.lmc(var_all, all, model = sph_fit)
plot(var_all, all_fit)
```




```
ck <- predict(all_fit, grd)
```

```
Linear Model of Coregionalization found. Good.
[using ordinary cokriging]
```

```
cok <- gstat.cv(all_fit)
```

```
Warning in checkNames(value): attempt to set invalid names: this may lead to
problems later on. See ?make.names
```

```
print(head(pred))
```

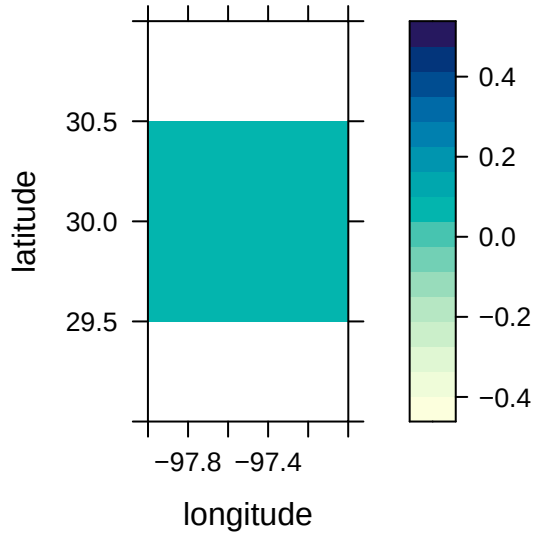
```
     var1.pred var1.var   observed    residual zscore fold longitude latitude
1  0.157460703       NA -0.1568927 -0.31435337     NA    1 -97.74668 30.27257
```

```
2  0.004633452       NA  0.2780841  0.27345065     NA    2 -97.72470 30.25387
3 -0.010727639       NA -0.2721183 -0.26139066     NA    3 -97.72851 30.24386
4 -0.105715907       NA -0.1266459 -0.02093003     NA    4 -97.74562 30.25795
5 -0.053681854       NA -0.1684152 -0.11473337     NA    5 -97.74712 30.27016
6  0.015238444       NA  0.2838454  0.26860694     NA    6 -97.72518 30.25520
```

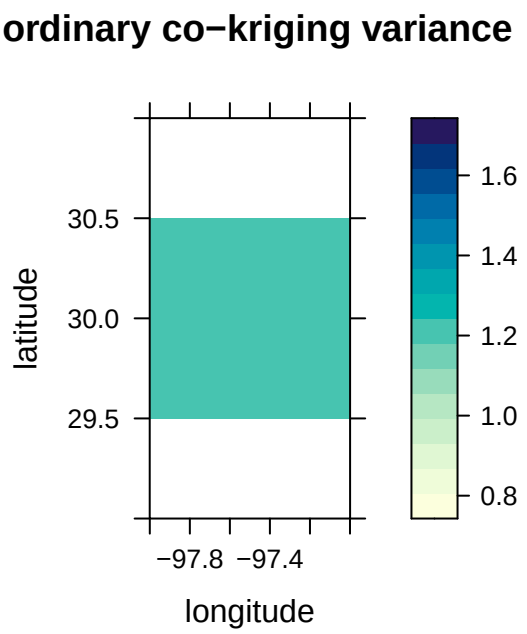
```
print(head(ck))
```

```
  longitude latitude scaled price.pred scaled price.var bathrooms.pred
1   -98.000       30        0.03859578         1.242966       0.086515
2   -97.999       30        0.03859578         1.242966       0.086515
3   -97.998       30        0.03859578         1.242966       0.086515
4   -97.997       30        0.03859578         1.242966       0.086515
5   -97.996       30        0.03859578         1.242966       0.086515
6   -97.995       30        0.03859578         1.242966       0.086515
  bathrooms.var cov.scaled price.bathrooms
1      1.073499                 0.2039032
2      1.073499                 0.2039032
3      1.073499                 0.2039032
4      1.073499                 0.2039032
5      1.073499                 0.2039032
6      1.073499                 0.2039032
```

```
library(lattice)

levelplot(ck$`scaled price.pred` ~ longitude + latitude, ck,
  aspect = "iso",
  main = "ordinary co-kriging predictions"
)
```




```
levelplot(ck$`scaled price.var` ~ longitude + latitude, ck,
  aspect = "iso",
  main = "ordinary co-kriging variance"
)
```



We can see lots of uniformity between the co-kriging predictions and variance. Is it better than ordinary kriging?

In this case, it looks like ordinary kriging is better as the cokriging results are too uniform and don't accurately capture the variation in pricing amongst Austin listings. Therefore, our final model is the spherical covariance model with ordinary kriging.

Ultimate Kriging Predictions

It should be noted that for the purposes of actual price prediction, the inputs of this model must be scaled which means that the resulting predictions have to be un-scaled to the original units.