Termpaper

Sindre og Morten

Oppgave 1

A

Hedoniske modeller blir tatt i bruk for å måle marginal «willingness to pay» (MWTP), denne blir tatt i bruk for å måle boligmarkedet sine miljømessige kvaliteter. Den hedoniske modellen ble fremstillt ved å ta i bruk et stort og avansert datasett fra boligmarkeder i store byer som har en avansert økonomi. Jo mer tilgang vi får på data til disse byområdene, desto bedre analyser får vi med bruk av en hedonisk modell.

Rosens første steg handler om å kunne definere et marked som vil tilfredstille «law of one function». «Law of one function» er at hus som er identiske blir solgt for den samme prisen i et gitt marked. Steg to handler om data innsamling. Det forteller oss at det er met oppnålig med å ha et tilfeldig utvalg. Slike datainnsamlinger til en hedonisk modell som omhandler eiendomsverdi har som regel fokus på eneboliger.

C - Why could it be important to define a housing market as a single metropolitan (or travel to work) area and studying a relatively short period of time, when estimating

i. hedonic price function?

Bishop forklarer at i hedonisk modell innebærer det at markedet bør defineres slik at «loven om en prisfunksjon» oppfylles (Bishop mfl. 2020). Med en prisfunksjon menes det at identiske boliger vil selges til samme pris gjennom hele markedet. Likevel, de nøyaktige romlige og tidsmessige grensene som tilfredsstiller denne betingelsen kan variere på tvers av rom og tid ettersom informasjon, institusjoner og flyttekostnader endres (Bishop mfl. 2020). I prakis er det vanlig å definere markedet som et enkelt storbyområde (single metropolian) over noen år. Flyttekostnader vil egentlig bryte med loven om en prisfunksjon, men for husholdninger som flytter innenfor dette storbyområdet er det lite sannsynlig at disse kostnadene vil variere noe særlig.

Årsaken til det er at de fysiske kostnadene som vel som de økonomiske (f.eks lastebil-leie) ikke endrer seg på tvers av destinasjonssteder i hovedstadsområdet. De psykologiske kostnadene er også mer begrenset ved flytting fordi det tillattes i lettere grad å opprettholde relasjonene til familie, venner og nabolag. Dette gjør at loven om én prisfunksjon opprettholdes mellom lokasjoner i et storbyområde gjennom arbitrasje. Altså, hvis to hus som er tilsvarende like i samme storbyområdet selges, så velger kjøperne naturligvis det rimeligste.

ii. Explain intuitively, by using an example, why it is important to avoid omitted variable bias when estimating a hedonic price model.

Gjennom empirien og teorien er det grunn til å tro av miljøfasiliteter er romlig korrelert på grunn av de naturlige trekkene ved geografien som for eksempel fjell og hav, miljøtilbakemeldingseffekter (f.eks urbane varme øyer) og stemming på lokale felles goder. Dette potensialet for romlig korrelasjon har ført til utbredt bekymring for utelatt-variabel skjevhet (Bishop mfl. 2020). Det er først og fremst fordi det virker usannsynlig at forskere vil være i stand til å inkludere alle bekvemmeligheter som betyr noe for kjøpere. I tillegg vil uobserverte fasiliteter sannsynligvis være korrelert med tilbudet av interesse, og dermed forårsake skjevhet. Dette kan forklares ved et eksempel: Hvis velstående og velutdannede boligkjøpere flytter til områder med bedre luftkvalitet og deretter stemmer for å øke offentlig skolefinansiering, vil estimater av MWTP for luftkvalitet være skjev oppover hvis skolekvalitet utelates fra modellen. Potensialet for denne typen oppførsel fra huseiere betyr at for at de resulterende estimatene skal være troverdige, må forskningsdesignet isolere eksogen variasjon i tilbudet av interesse (Bishop mfl. 2020).

Oppgave 2

i.

Så over variablene og definisjonene på dem hos Kaggle.

ii.

Laster inn data

```r
kc_house_data <- read_csv("kc_house_data.csv")
```

```
Rows: 21613 Columns: 21
-- Column specification --------------------------------------------------------
Delimiter: ","
chr   (1): id
```

```
dbl  (19): price, bedrooms, bathrooms, sqft_living, sqft_lot, floors, waterf...
dttm  (1): date

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.
```

iii.

```r
kc_house_data <- arrange(kc_house_data, desc(date))
```

iv.

```r
kc_house_data <- kc_house_data %>%
  distinct(id, .keep_all = TRUE)
```

v & vi.

```r
kc_house_data_sf <- st_as_sf(kc_house_data,
                             coords = c(x = "long",
                                        y = "lat"),
                             crs = 4326) %>%
  st_transform(2926)
```

vii.

koordinatene til Seattle:

Norske (wikepedia):

- 47.60621, -122.33207

Engelske (wikepedia):

- 47.609722, -122.333056

```r
cbd <- st_sfc(st_point(c(-122.33207, 47.60621)), crs = 4326) %>%
  st_transform(2926)
```

viii.

```r
kc_house_data_sf <-  kc_house_data_sf %>%
  mutate(dist_cbd = st_distance(cbd, .,
                                by_element = TRUE),
    dist_cbd_km = set_units(dist_cbd, km)
  )
```

Oppgave 3

```r
kc_wadoh_map <- here("maps/WADOH_Environmental_Health_Disparities_Index_Calculated_for_Kin
      st_read() %>%
  st_transform(2926)
```

```
Reading layer `WADOH_Environmental_Health_Disparities_Index_Calculated_for_King_County___wad
  using driver `ESRI Shapefile'
Simple feature collection with 398 features and 192 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -122.528 ymin: 47.08446 xmax: -121.0657 ymax: 47.78058
Geodetic CRS:  WGS 84
```

```r
kc_wadoh_map <- kc_wadoh_map %>%
  select(
  GEO_ID_TRT,
  EHD_percen,#Environmental Health Index, weighted score many vars
  linguist_2,#Pop. age 5+ speaking English less than "very well"
  poverty_pe,#Percentage people living in poverty
  POC_percen,#People of Color in percentage of pop. in tract
  transporta,#% of income spent on transportation median family in tract
  unemploy_2,#percentage unemployed
  housing_pe,#% of households in group "Unaffordable Housing" (>30% inc.)
  traffic_pe,#% of pop. near heavy traffic roadways
  diesel,# nox consentration
  ozone,# ozone consentration
  PM25, # consentration of Particulate Matter in air
  toxic_rele, # Toxic release from factories
  hazardous_, # Hazardous Waste Treatment Storage and disposal Facilities
  lead_perce, # measure of Lead paint in houses
```

```r
    superfund, # Proximity to contaminated sites on national list
    facilities, # Proximity to Risk Management Plan Facilities
    wastewater, # Proximity to wastewater facilities
    sen_pop_pe, # % pop. over 65
    socio_perc # score social economic determants, low best
    )
```

```r
acs_b19101_fam_inc <- read.dbf("../maps/censusSHP/acs_b19101_familyincome.dbf")
attach(acs_b19101_fam_inc)
```

```r
acs_b19101_fam_inc <- acs_b19101_fam_inc %>%
    mutate(low = (E19101138 + E19101139 + E19101140 + E19101141 +
                      E19101142 + E19101143)/E19101137) %>%
    mutate(mid = (E19101144 + E19101145 + E19101146 + E19101147 +
                      E19101148 + E19101149)/E19101137) %>%
    mutate(high = (E19101150 + E19101151 + E19101152 + E19101153)/E19101137)
```

```r
acs_b19101_fam_inc <- acs_b19101_fam_inc %>%
    select(GEOIDTRT, low, mid, high) %>%
    rename(GEO_ID_TRT = GEOIDTRT)
```

```r
kc_wadoh_map_2 <- left_join(
    acs_b19101_fam_inc,
    st_drop_geometry(kc_wadoh_map),
    by = "GEO_ID_TRT")
```

```r
kc_tracts10 <- here("../maps/censusSHP/tracts10.shp") %>%
  st_read() %>%
  st_transform(2926)
```

```
Reading layer `tracts10' from data source
  `/Users/Morten/Documents/Boligmarked/maps/censusSHP/tracts10.shp'
  using driver `ESRI Shapefile'
Simple feature collection with 398 features and 22 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 1217085 ymin: 31406.52 xmax: 1583210 ymax: 287947.2
Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

```r
kc_tracts10_shore <- here("../maps/censusSHP/tracts10_shore.shp") %>%
  st_read() %>%
  st_transform(2926)
```

```
Reading layer `tracts10_shore' from data source
  `/Users/Morten/Documents/Boligmarked/maps/censusSHP/tracts10_shore.shp'
  using driver `ESRI Shapefile'
Simple feature collection with 398 features and 22 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 1220306 ymin: 31406.52 xmax: 1583210 ymax: 287675.5
Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

```r
kc_tracts10_env_data <- left_join(
  kc_tracts10, kc_wadoh_map_2,
  by = "GEO_ID_TRT"
  )
kc_tracts10_shore_env_data <- left_join(
  kc_tracts10_shore, kc_wadoh_map_2,
  by = "GEO_ID_TRT"
  )
```

```r
kc_houses_env_var <- st_join(kc_house_data_sf, kc_tracts10_env_data)
kc_tracts10_shore_env_var <- st_join(kc_house_data_sf, kc_tracts10_shore_env_data)
```

```r
st_write(kc_house_data, "../maps/kc_house_data.gpkg", append = FALSE)
```

```
Deleting layer `kc_house_data' using driver `GPKG'
Writing layer `kc_house_data' to data source
  `../maps/kc_house_data.gpkg' using driver `GPKG'
Writing 21436 features with 21 fields without geometries.
```

```r
st_write(kc_tracts10, "../maps/kc_tracts10.gpkg", append = FALSE)
```

```
Deleting layer `kc_tracts10' using driver `GPKG'
Writing layer `kc_tracts10' to data source
  `../maps/kc_tracts10.gpkg' using driver `GPKG'
Writing 398 features with 22 fields and geometry type Polygon.
```

```r
st_write(kc_tracts10_shore, "../maps/kc_tracts10_shore.gpkg", append = FALSE)
```

```
Deleting layer `kc_tracts10_shore' using driver `GPKG'
Writing layer `kc_tracts10_shore' to data source
  `../maps/kc_tracts10_shore.gpkg' using driver `GPKG'
Writing 398 features with 22 fields and geometry type Multi Polygon.
```

```r
st_write(kc_houses_env_var, "../maps/kc_houses_env_var.gpkg", append = FALSE)
```

```
Deleting layer `kc_houses_env_var' using driver `GPKG'
Writing layer `kc_houses_env_var' to data source
  `../maps/kc_houses_env_var.gpkg' using driver `GPKG'
Writing 21436 features with 65 fields and geometry type Point.
```

```r
st_write(kc_tracts10_shore_env_var, "../maps/kc_tracts10_shore_env_var.gpkg", append = FAL
```

```
Deleting layer `kc_tracts10_shore_env_var' using driver `GPKG'
Writing layer `kc_tracts10_shore_env_var' to data source
  `../maps/kc_tracts10_shore_env_var.gpkg' using driver `GPKG'
Writing 21436 features with 65 fields and geometry type Point.
```

Oppgave 4

i.

```r
#summary(kc_tracts10_env_data) <- La til hashtag for å unngå render-problemer
```

```r
#summary(kc_tracts10_shore_env_var) <- La til hashtag for å unngå render-problemer
```

ii.

I QGIS fant vi følgende observasjoner ved å se på *tracts10*, *tracts10_shore* & *kc_houses_env_var*:

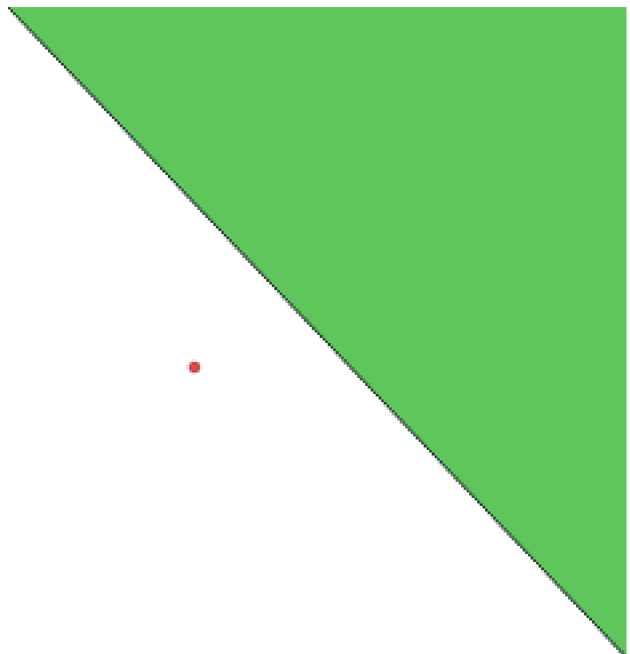


Figure 1: observasjon utenfor WA state

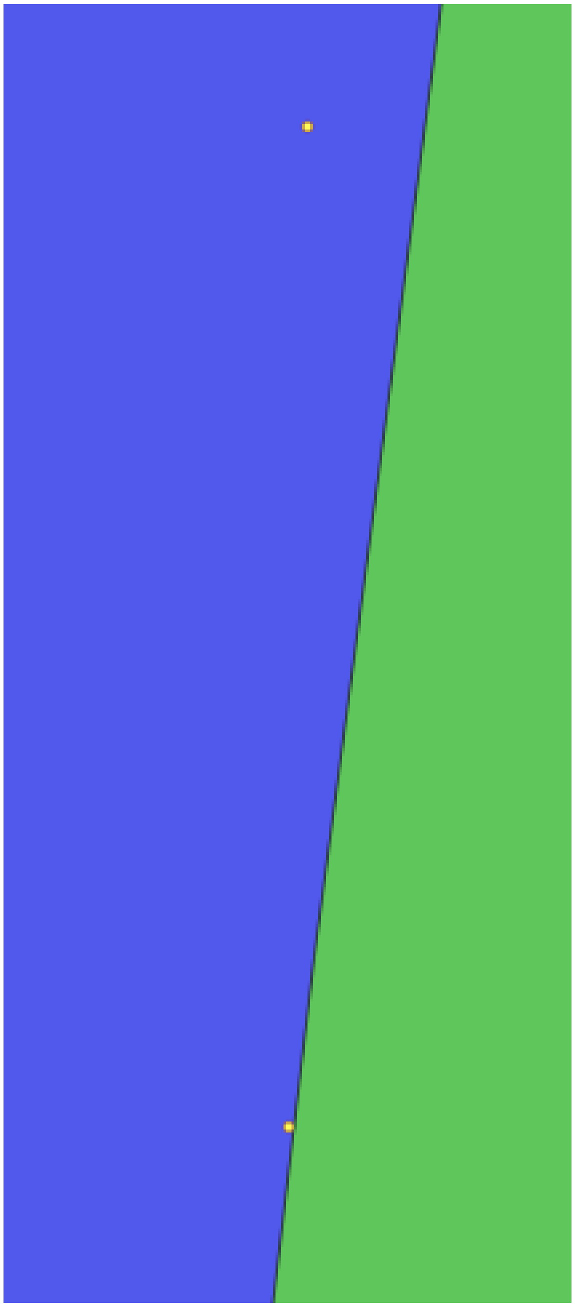


Figure 2: Observasjon utenfor kystlinjen.a

Figure 3: Observasjon utenfor kystlinjen.b

iii.

Dropper Observasjonen 3518000180 ved å:

```
kc_houses_env_var <- arrange(kc_houses_env_var, desc(id))
kc_houses_env_var_omit <- kc_houses_env_var[-c(11997),]
```

```
st_write(kc_houses_env_var_omit, "../maps/kc_houses_env_var_omit.gpkg", append = FALSE)
```

```
Deleting layer `kc_houses_env_var_omit' using driver `GPKG'
Writing layer `kc_houses_env_var_omit' to data source
  `../maps/kc_houses_env_var_omit.gpkg' using driver `GPKG'
Writing 21435 features with 65 fields and geometry type Point.
```

```
kc_houses_env_var_omit <- kc_houses_env_var_omit %>%
    mutate(
        year_month = substr(date, start = 1, stop = 7))
```

```
st_write(kc_houses_env_var_omit, "../maps/kc_houses_env_var_omit.gpkg", append = FALSE)
```

```
Deleting layer `kc_houses_env_var_omit' using driver `GPKG'
Writing layer `kc_houses_env_var_omit' to data source
  `../maps/kc_houses_env_var_omit.gpkg' using driver `GPKG'
Writing 21435 features with 66 fields and geometry type Point.
```

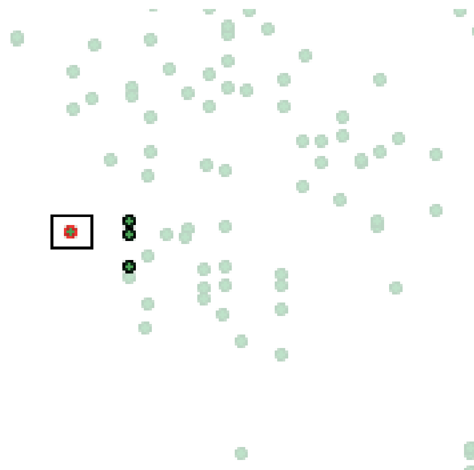


Figure 4: K-nearest 3

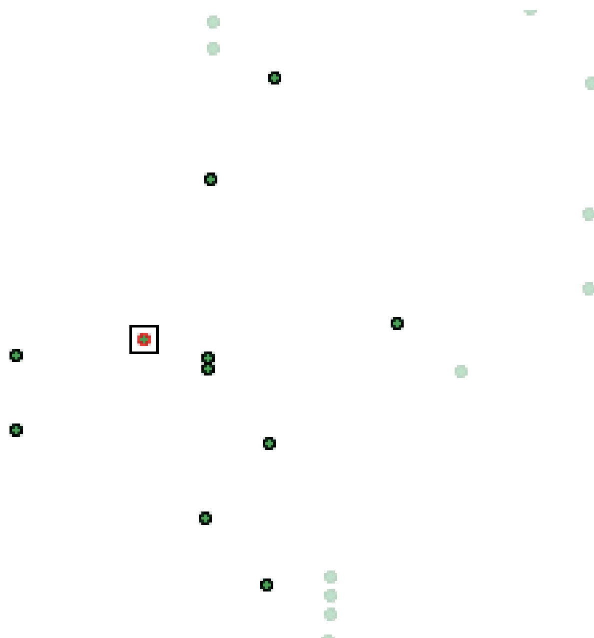


Figure 5: K-nearest 10

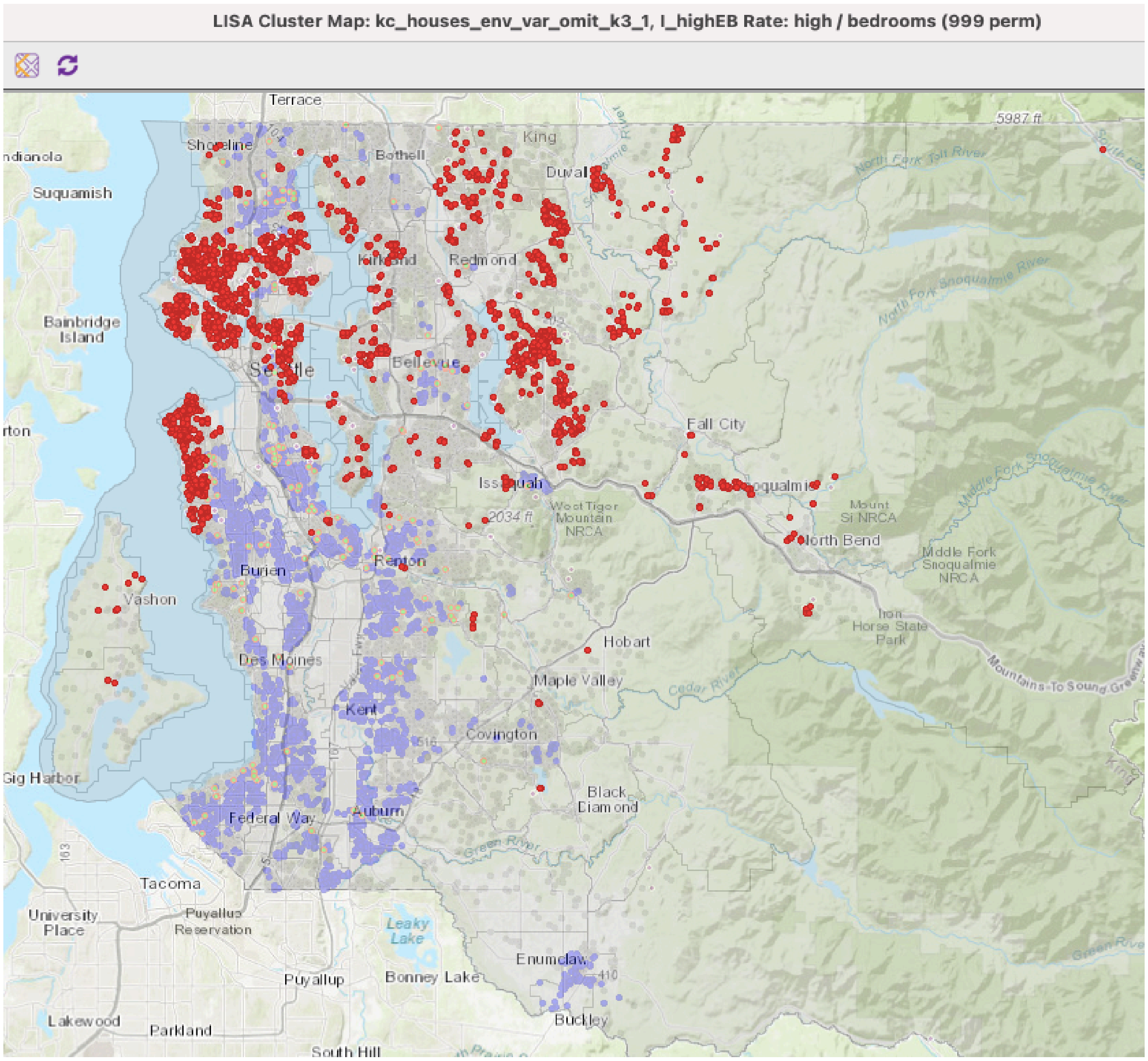


Figure 6: K3 - Store og dyre boliger

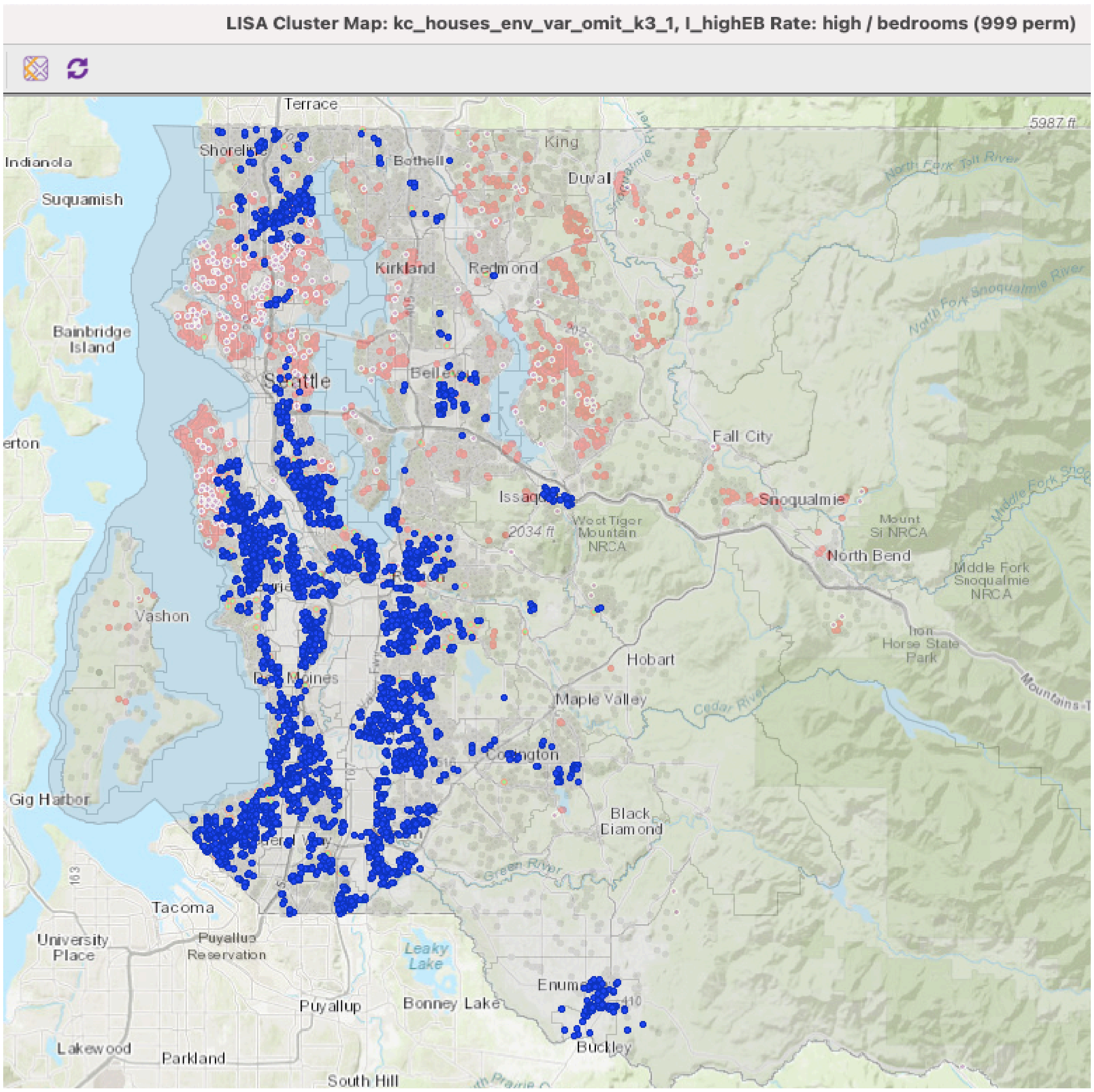


Figure 7: K3 - Små og billige boliger

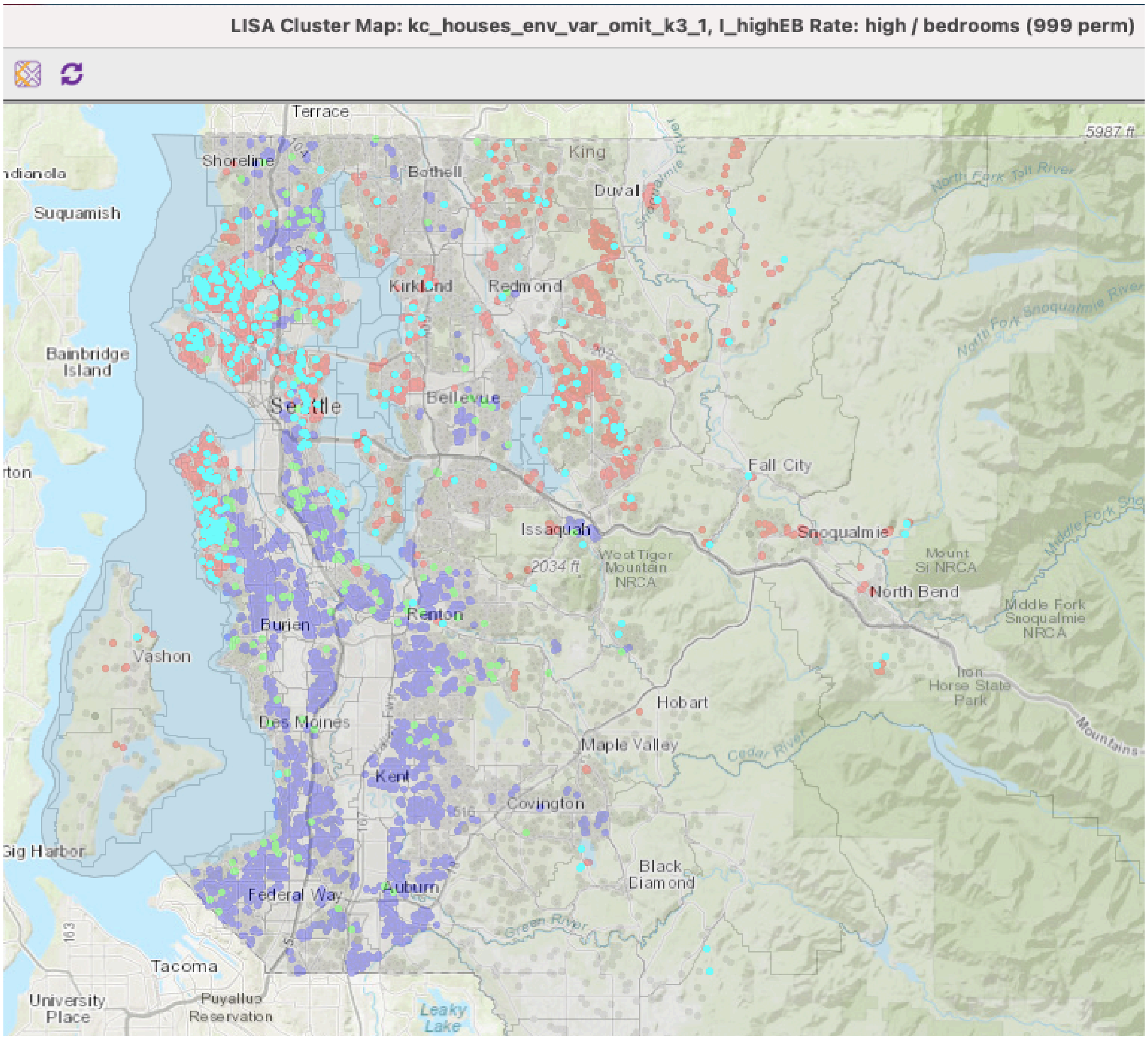


Figure 8: K3 - Små og dyre boliger

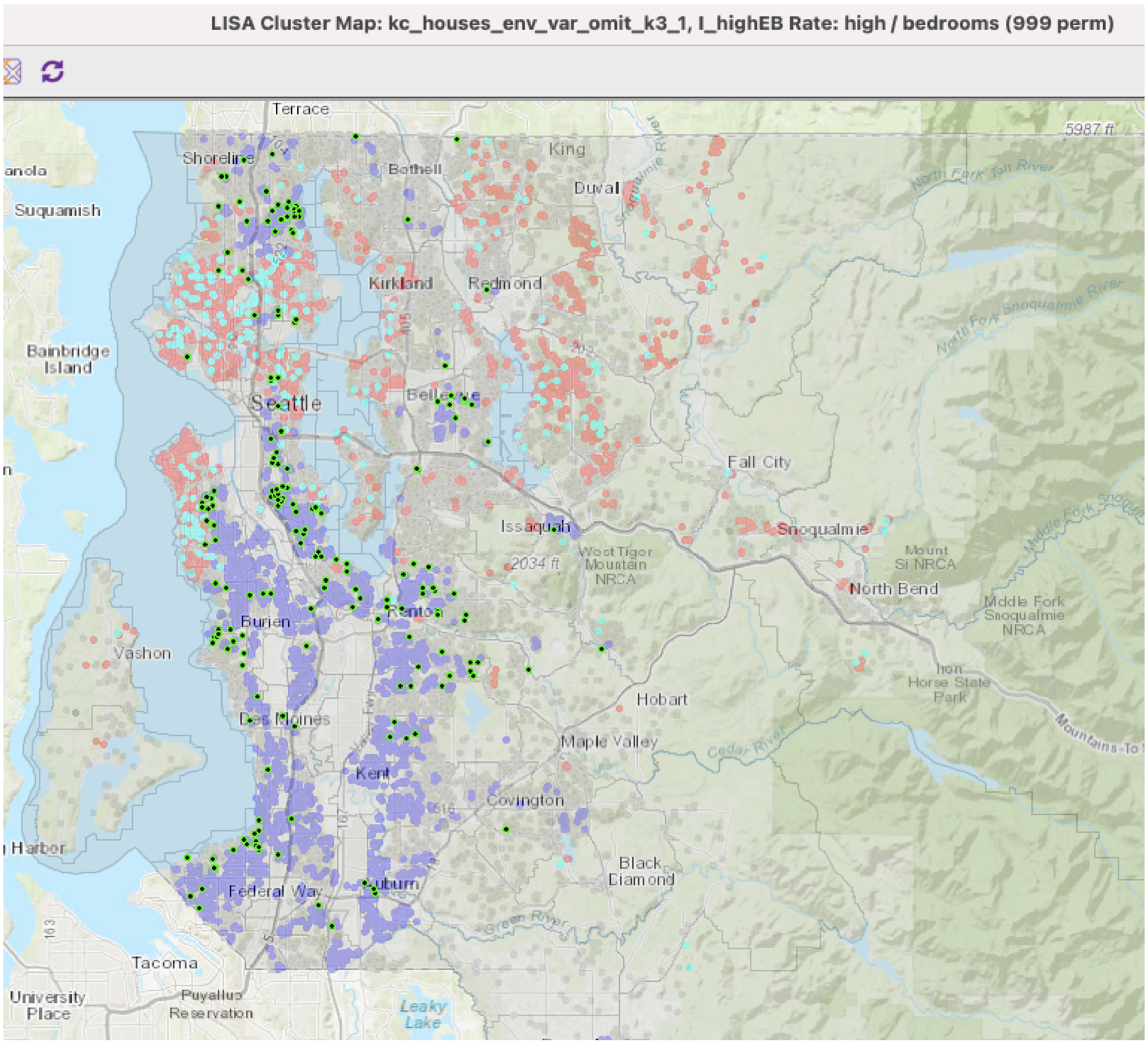


Figure 9: K3 - Store og billige boliger

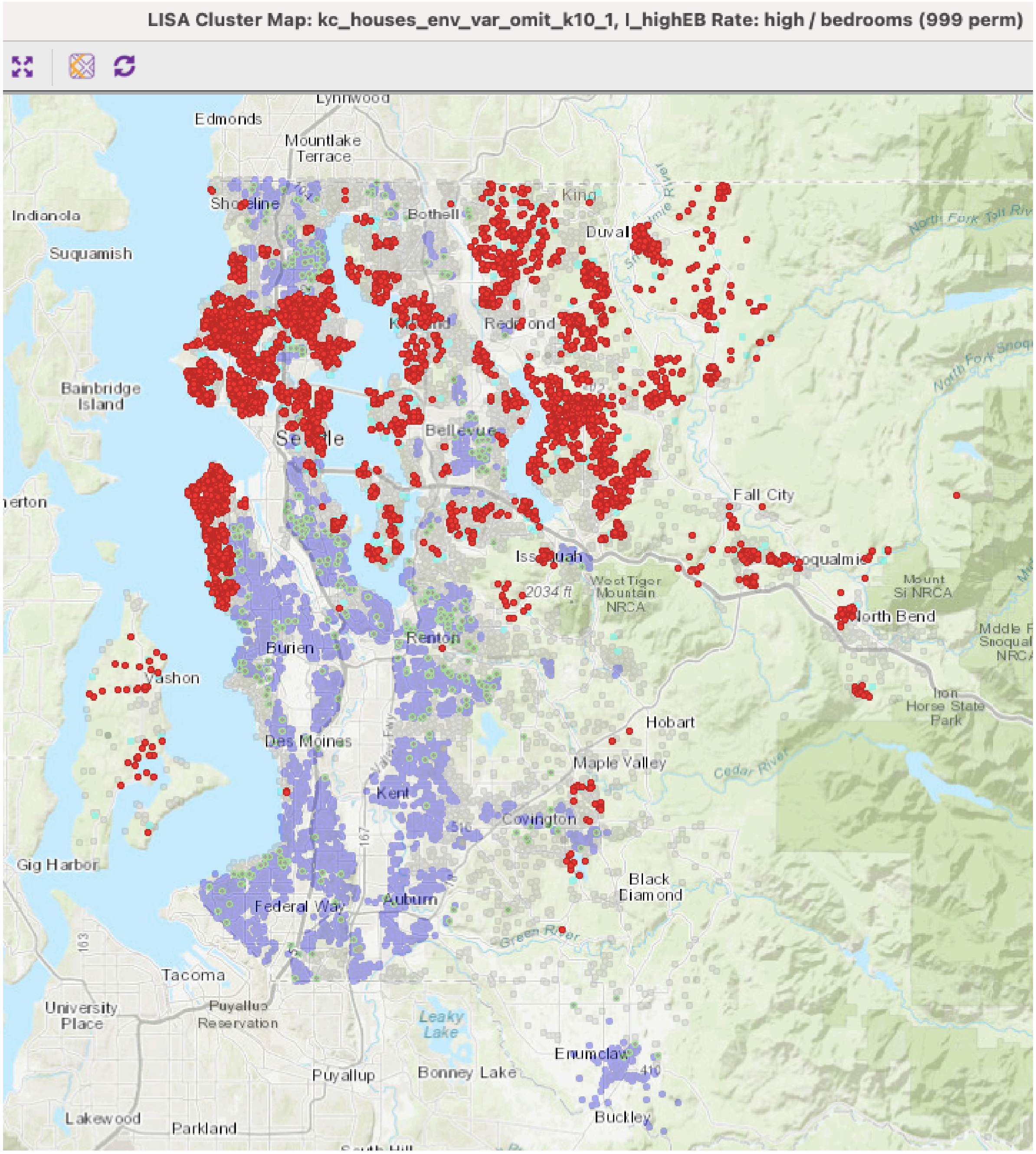


Figure 10: K10 - Store og dyre boliger

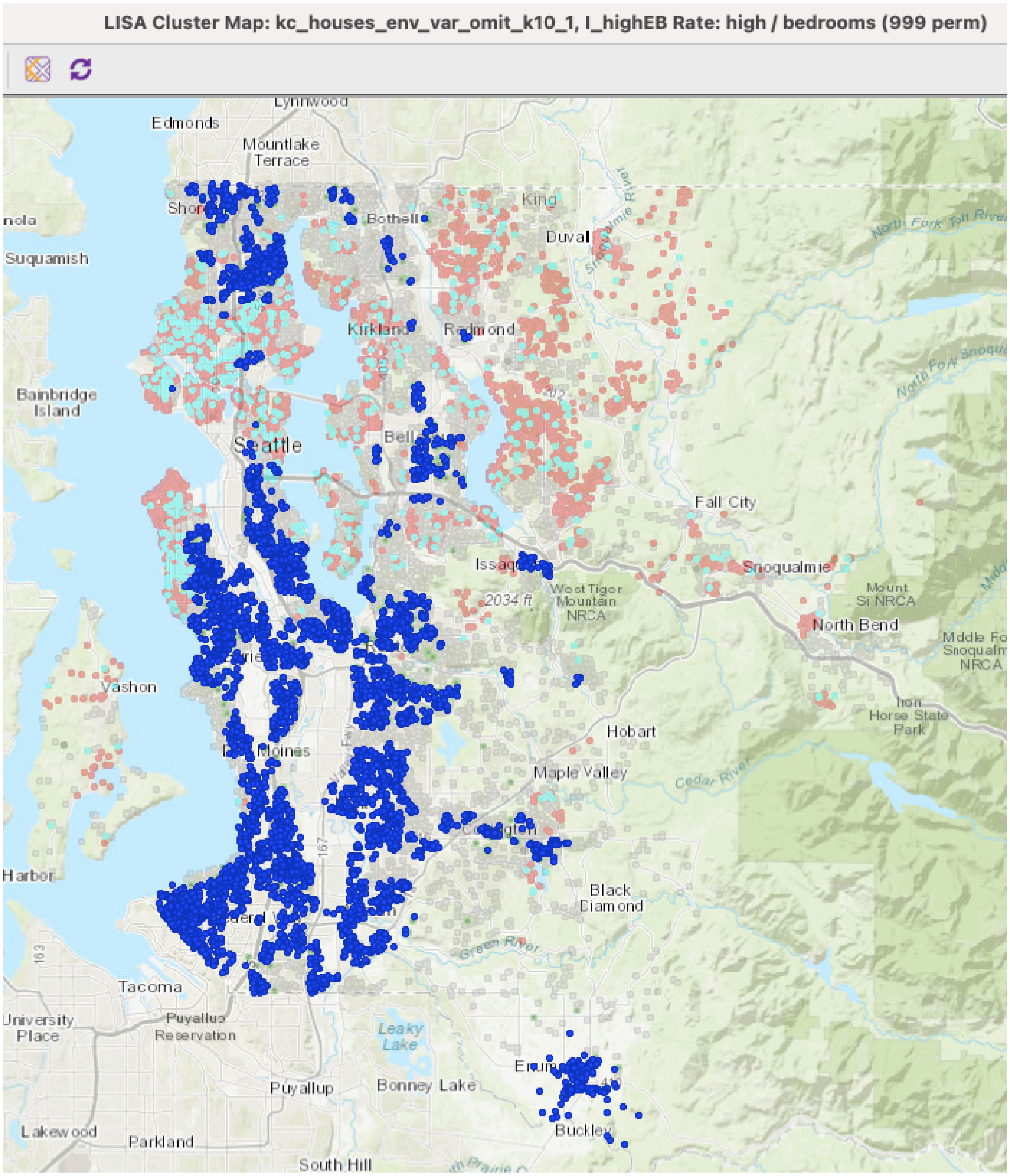


Figure 11: K10 - Små og billige boliger

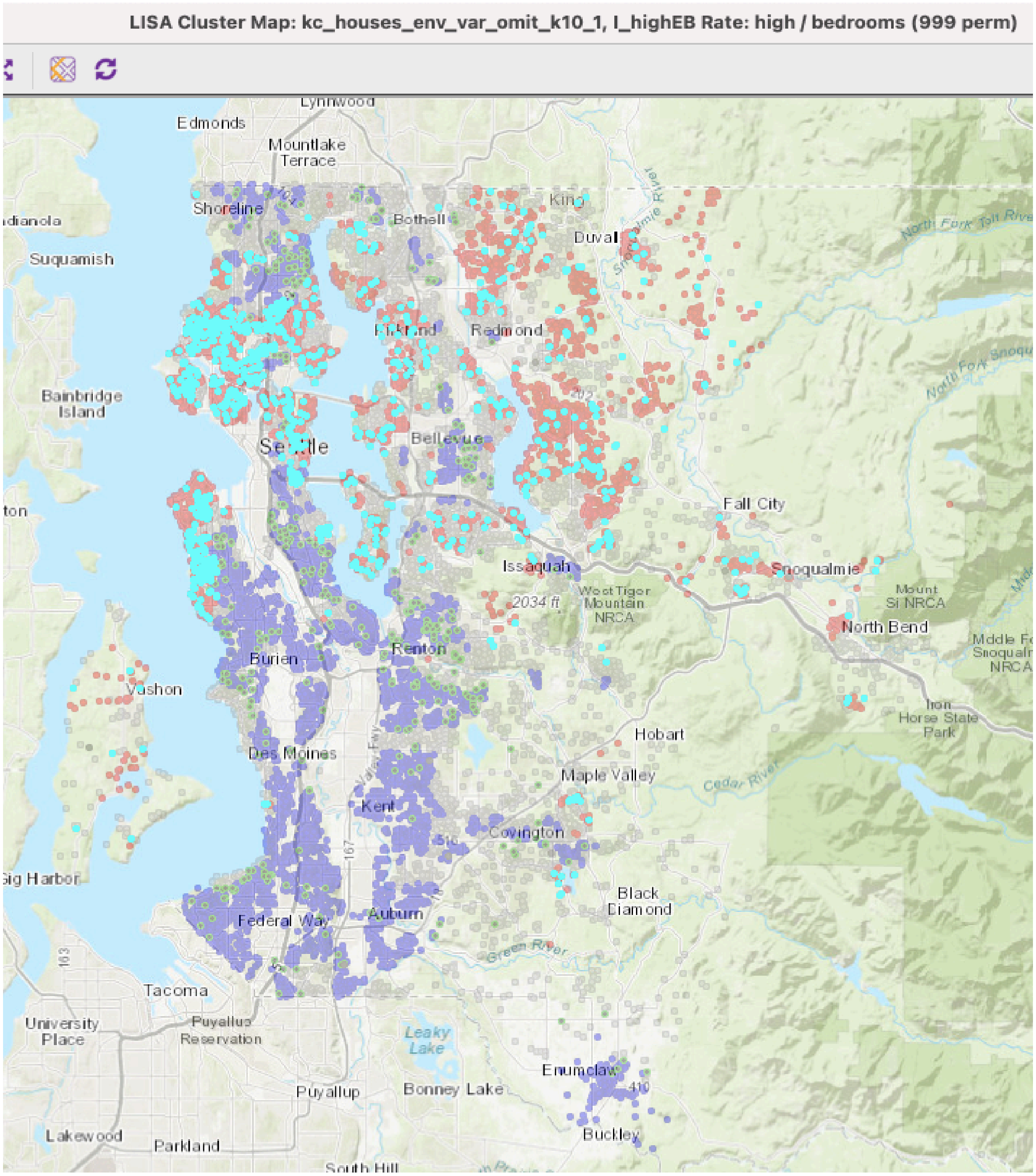


Figure 12: K10 - Små og dyre boliger

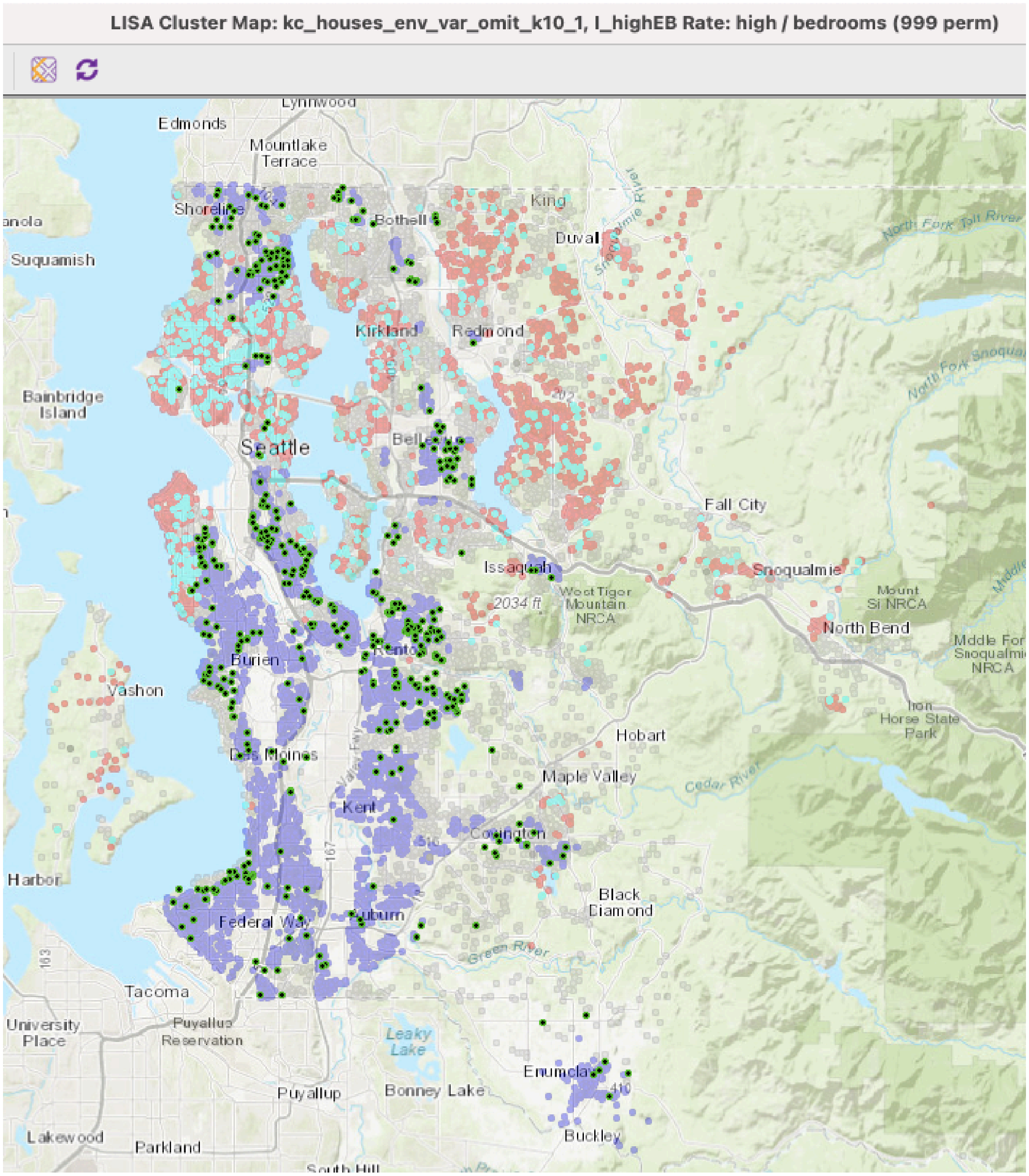


Figure 13: K10 - Store og billige boliger

Oppgave 5

Oppgave 6

i)

```r
attach(kc_houses_env_var_omit)
```

i. Huskarakteristika

```r
mod1 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_living15 + sqft_lot + sqft_lot1
```

ii. Huskarakteristika + distanse til cbd + tracts_var

```r
mod2 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_living15 + sqft_lot + sqft_lot1
hazardous_ + lead_perce + socio_perc"
```

iii. Huskarakteristika + distanse til cbd + EHD

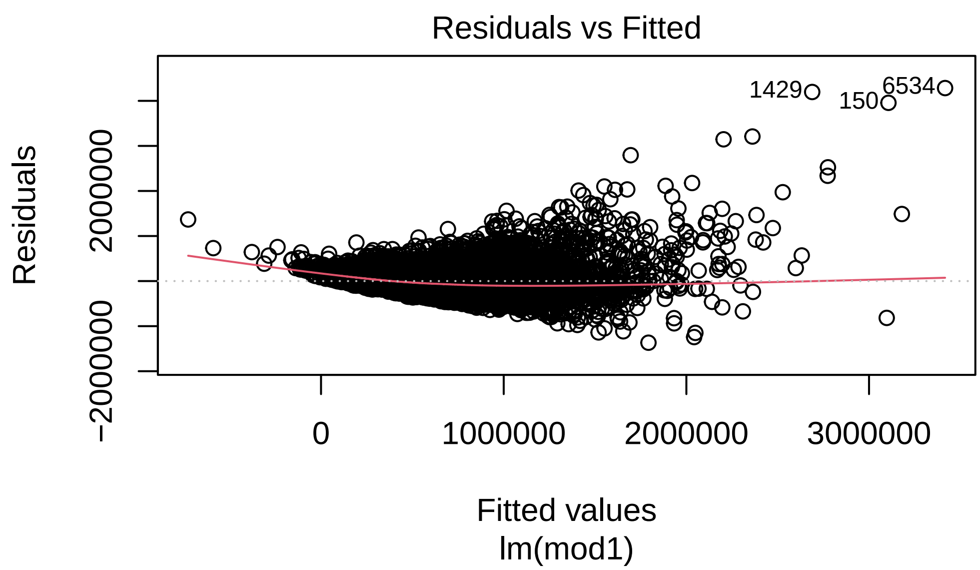
```r
mod3 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_living15 + sqft_lot + sqft_lot1
```

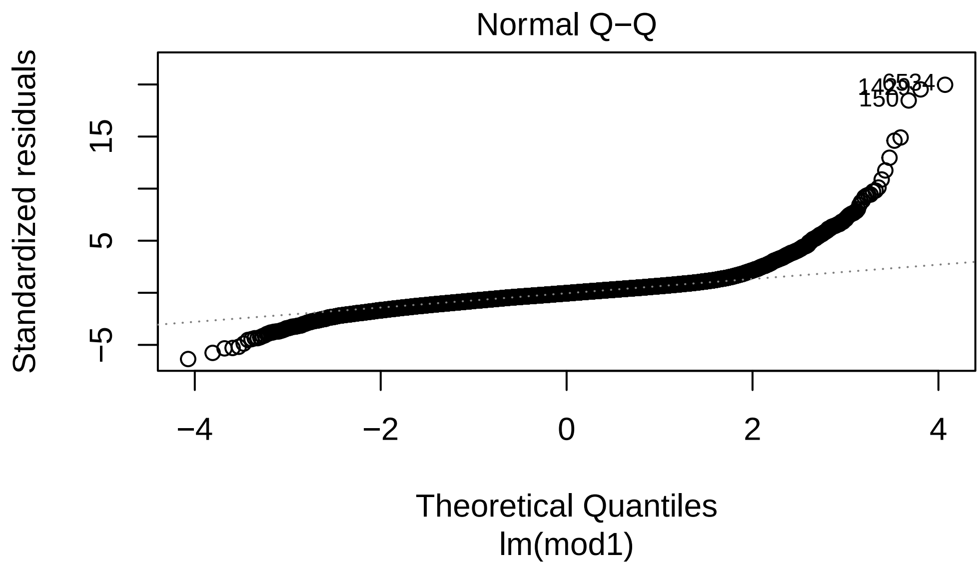
```r
hedon1 <- lm(mod1, data = kc_houses_env_var_omit)
hedon2 <- lm(mod2, data = kc_houses_env_var_omit)
hedon3 <- lm(mod3, data = kc_houses_env_var_omit)
```

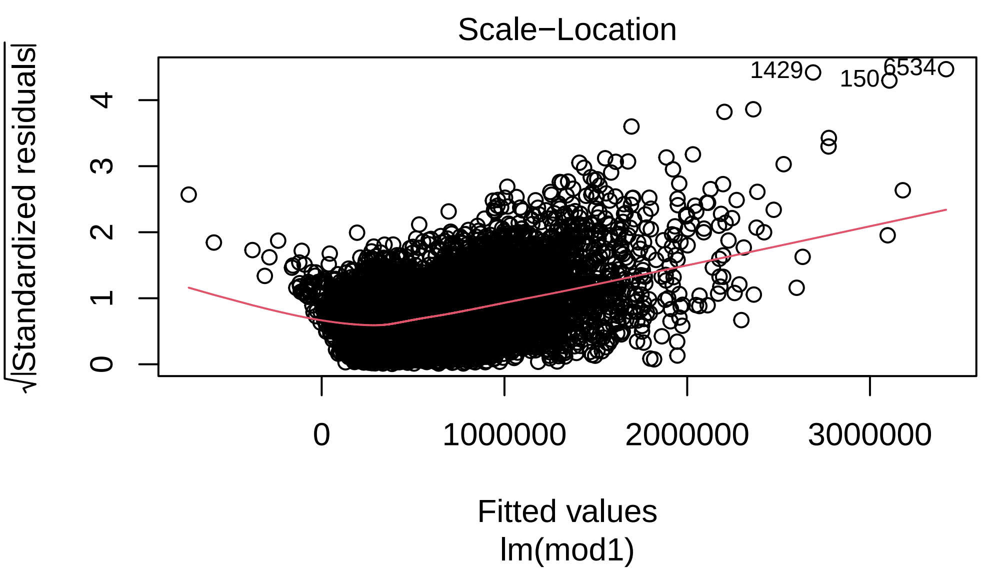
```r
huxreg("Hedon1" = hedon1, "Hedon2" = hedon2, "Hedon3" = hedon3,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

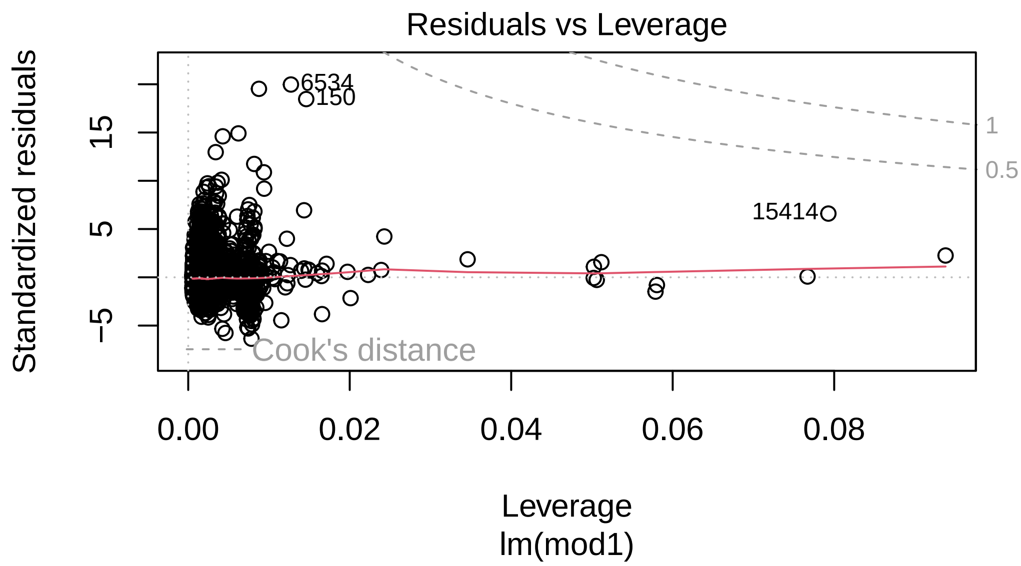
Plots

```
hedon1 %>%
  plot()
```

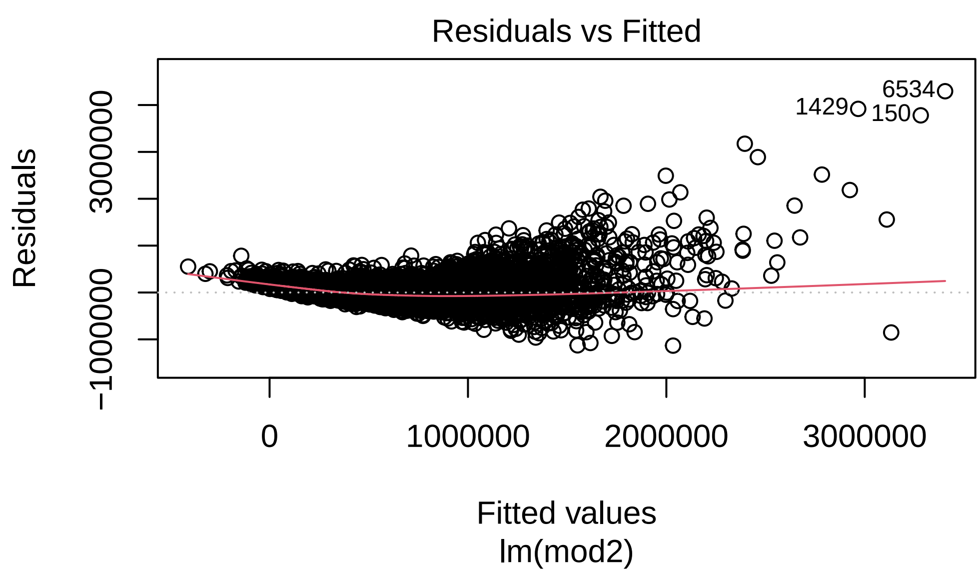


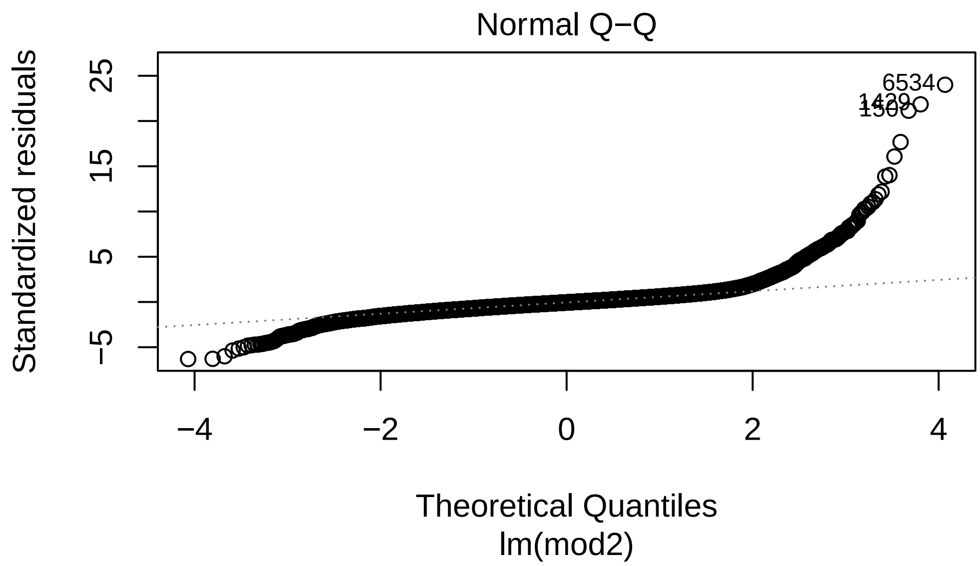

Normal Q−Q
Standardized residuals
−5
5
15
−4
−2
0
2
4
Theoretical Quantiles
lm(mod1)
1429
6534
150

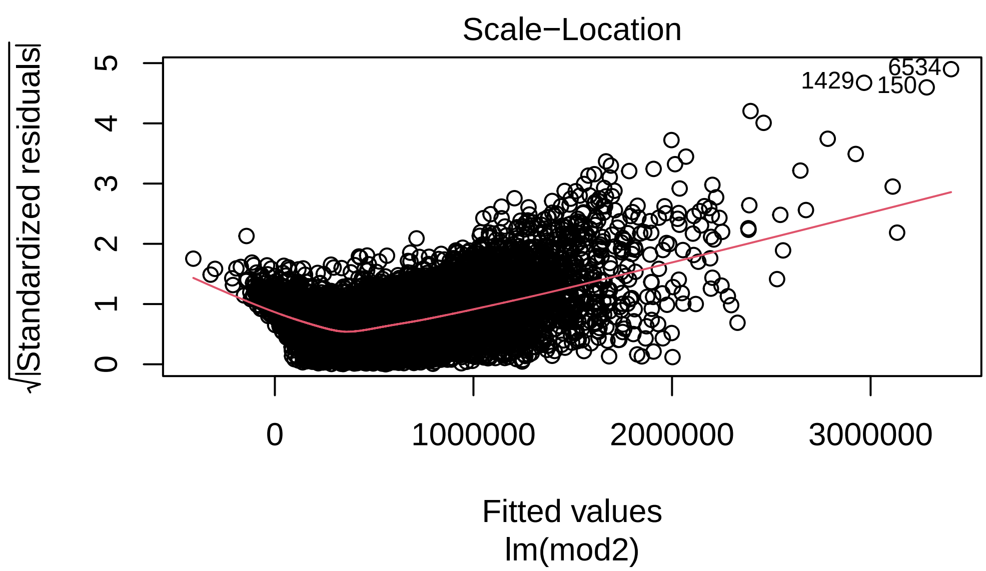

Scale−Location
√|Standardized residuals|
0
1
2
3
4
0
1000000
2000000
3000000
Fitted values
lm(mod1)
1429
150
6534

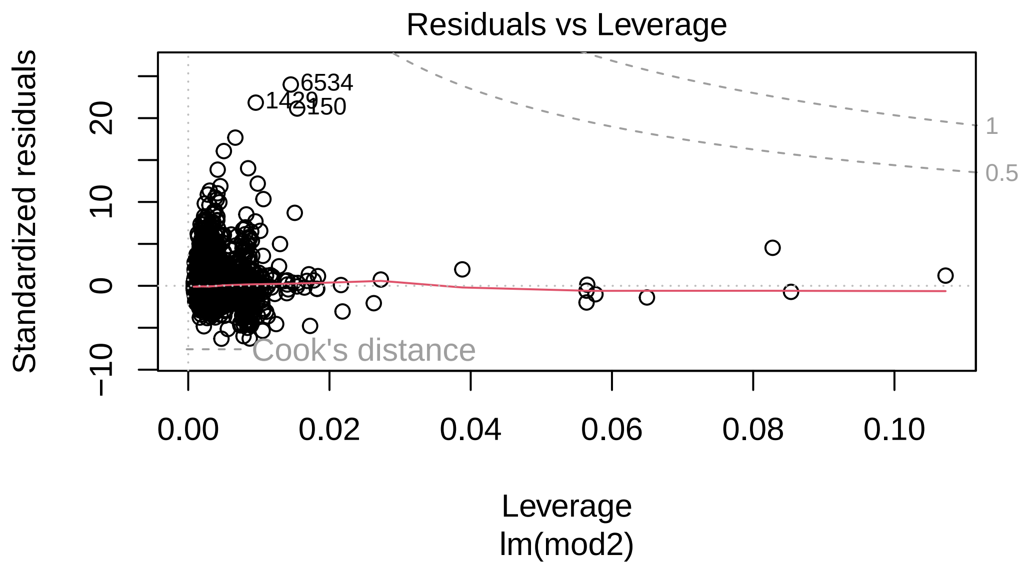

Residuals vs Leverage
Standardized residuals
−5
5
15
6534
150
15414
1
0.5
Cook's distance
0.00
0.02
0.04
0.06
0.08
Leverage
lm(mod1)

```
hedon2 %>%
  plot()
```

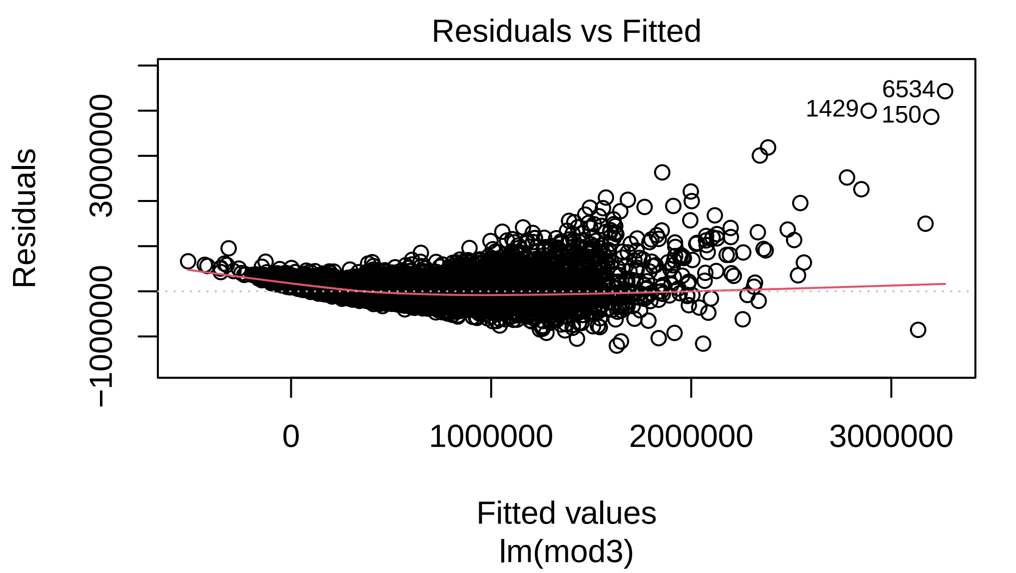

Residuals vs Fitted
Residuals
−1000000
3000000
6534
1429
150
0
1000000
2000000
3000000
Fitted values
lm(mod2)

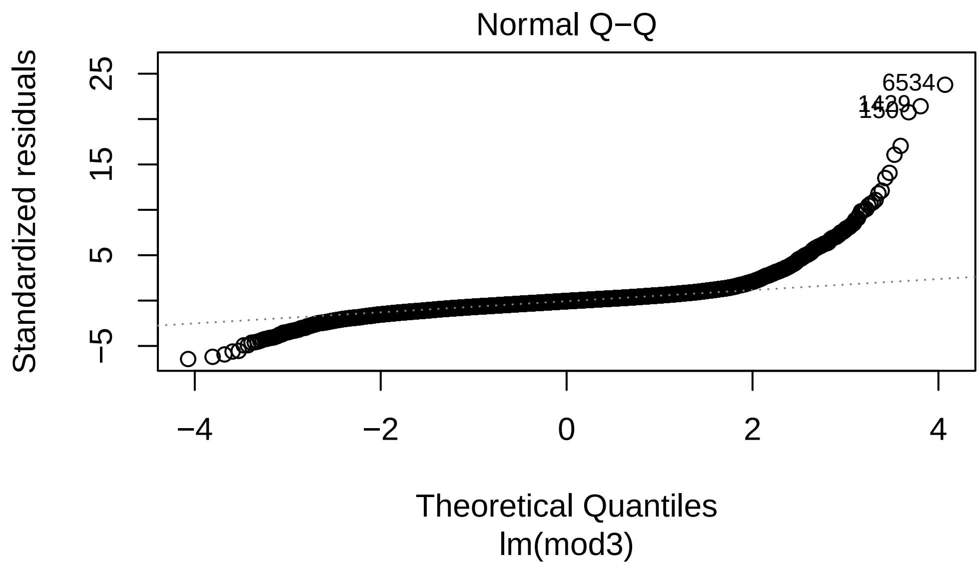

Normal Q−Q
Standardized residuals
−5
5
15
25
−4
−2
0
2
4
6534
1429
150
Theoretical Quantiles
lm(mod2)

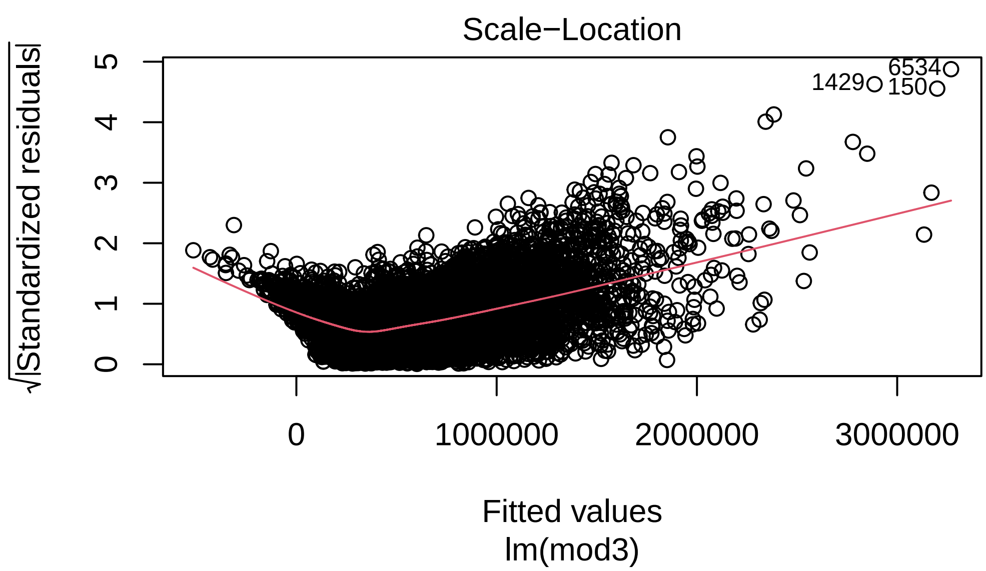

Scale−Location
√|Standardized residuals|
0
1
2
3
4
5
0
1000000
2000000
3000000
1429
6534
150
Fitted values
lm(mod2)

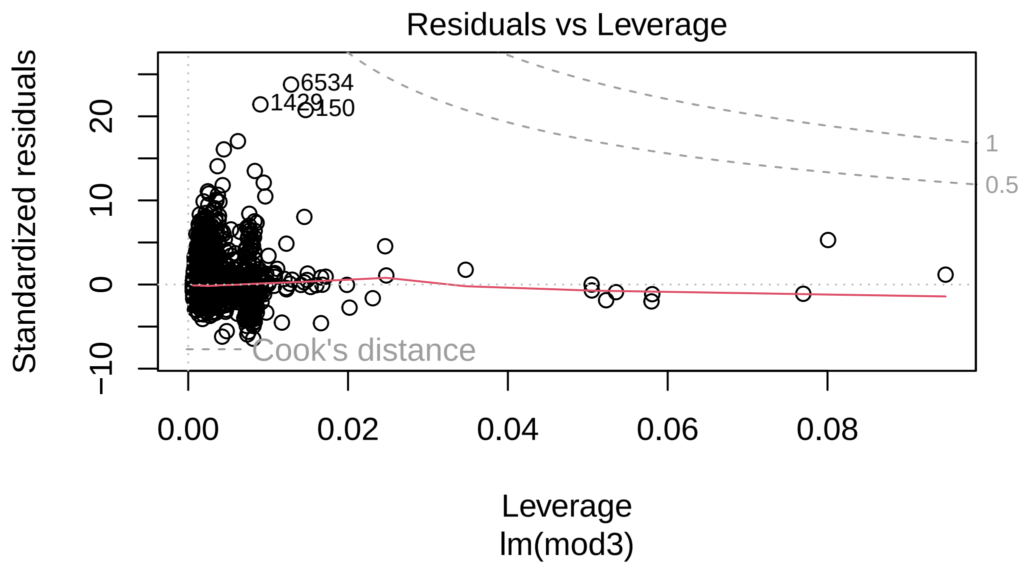

Residuals vs Leverage
Standardized residuals
Leverage
lm(mod2)
Cook's distance
6534
1429
150
1
0.5
−10
0
10
20
0.00
0.02
0.04
0.06
0.08
0.10

```
hedon3 %>%
  plot()
```


Residuals vs Fitted
Residuals
Fitted values
lm(mod3)
6534
1429
150
−1000000
1000000
3000000
0
1000000
2000000
3000000


Normal Q−Q
Standardized residuals
−5
5
15
25
6534
1429
150
−4
−2
0
2
4
Theoretical Quantiles
lm(mod3)


Scale−Location
√|Standardized residuals|
0
1
2
3
4
5
6534
1429
150
0
1000000
2000000
3000000
Fitted values
lm(mod3)



Oppgave 7

```
hedon1 %>%
    linearHypothesis(c("year_month2014-06=0", "year_month2014-07=0",
                       "year_month2014-08=0", "year_month2014-09=0",
                       "year_month2014-10=0", "year_month2014-11=0",
                       "year_month2014-12=0", "year_month2015-01=0",
                       "year_month2015-02=0", "year_month2015-03=0",
                       "year_month2015-04=0", "year_month2015-05=0"),
                     white_adjust = hc3)
```

```
hedon2 %>%
    linearHypothesis(c("year_month2014-06=0", "year_month2014-07=0",
                       "year_month2014-08=0", "year_month2014-09=0",
                       "year_month2014-10=0", "year_month2014-11=0",
                       "year_month2014-12=0", "year_month2015-01=0",
                       "year_month2015-02=0", "year_month2015-03=0",
                       "year_month2015-04=0", "year_month2015-05=0"),
                     white_adjust = hc4)
```

```
hedon3 %>%
    linearHypothesis(c("year_month2014-06=0", "year_month2014-07=0",
                        "year_month2014-08=0", "year_month2014-09=0",
                        "year_month2014-10=0", "year_month2014-11=0",
                        "year_month2014-12=0", "year_month2015-01=0",
                        "year_month2015-02=0", "year_month2015-03=0",
                        "year_month2015-04=0", "year_month2015-05=0"),
                      white_adjust = hc1)
```

Oppgave 8

kommer i morgen kl 12.

References

Bishop, Kelly C., Nicolai V. Kuminoff, H. Spencer Banzhaf, Kevin J. Boyle, Kathrine von Gravenitz, Jaren C. Pope, V. Kerry Smith, og Christopher D. Timmins. 2020. «Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality». *Review of Environmental Economics and Policy* 14 (2): 260–81. https://doi.org/10.1093/reep/reaa001.

	Hedon1	Hedon2	Hedon3
(Intercept)	6210567.524 ***	657425.366 ***	2074345.166 ***
	[44.647]	[4.108]	[15.526]
bedrooms	-39596.759 ***	-25163.513 ***	-29199.967 ***
	[-19.444]	[-14.598]	[-16.453]
bathrooms	46467.945 ***	27772.322 ***	32447.960 ***
	[13.256]	[9.384]	[10.639]
sqft_living	167.682 ***	126.046 ***	134.430 ***
	[35.847]	[31.602]	[32.759]
sqft_living15	24.038 ***	31.234 ***	9.229 **
	[6.662]	[9.720]	[2.844]
sqft_lot	-0.003	0.241 ***	0.233 ***
	[-0.061]	[5.319]	[5.220]
sqft_lot15	-0.556 ***	-0.138 *	-0.195 **
	[-7.100]	[-2.007]	[-2.833]
sqft_above	-6.495	90.821 ***	70.970 ***
	[-1.426]	[22.508]	[17.279]
floors	26914.959 ***	-65359.964 ***	-36017.276 ***
	[7.100]	[-18.842]	[-10.617]
grade	120002.514 ***	63525.892 ***	71466.335 ***
	[53.176]	[31.615]	[34.921]
yr_built	-3584.346 ***	-627.660 ***	-1280.600 ***
	[-50.313]	[-8.454]	[-18.447]
yr_renovated	10.616 **	29.414 ***	26.091 ***
	[2.706]	[8.830]	[7.631]
waterfront	579243.823 ***	616493.521 ***	606497.213 ***
	[31.092]	[39.274]	[37.453]
condition	20271.885 ***	31613.818 ***	31697.477 ***
	[8.057]	[14.719]	[14.398]
view	42889.032 ***	46953.183 ***	46131.828 ***
	[18.823]	[24.228]	[23.287]
year_month2014-06	3436.683	8283.718	7438.343

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.14e+04	1e+15				
2.14e+04	9.97e+14	12	5.35e+12	9.57	7.55e-19

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.12e+04	6.93e+14				
2.12e+04	6.87e+14	12	5.79e+12	14.9	1.29e-31

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.14e+04	7.59e+14				
2.14e+04	7.53e+14	12	5.98e+12	14.2	6.19e-30