

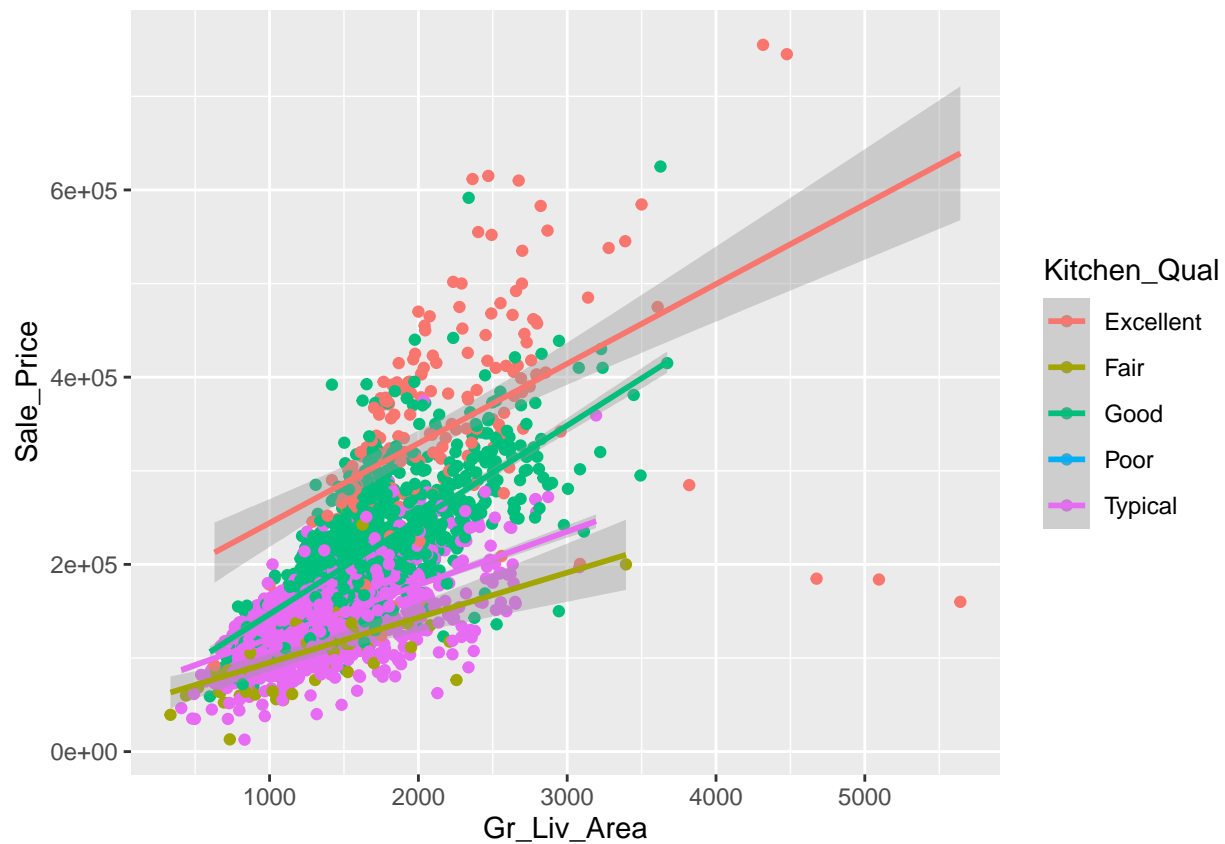
module3

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Part 1

Use this script to make a limited version of the AmesHousing Dataset and make a quick scatterplot and linear model.



```
##
## Call:
## lm(formula = Sale_Price ~ ., data = Ames_small)
##
## Coefficients:
##      (Intercept)      Gr_Liv_Area      Central_AirY
##      2265184.67         77.69         40945.69
## Kitchen_QualFair Kitchen_QualGood Kitchen_QualPoor
```

```
##           -144273.35           -90505.83           -119301.88
## Kitchen_QualTypical           Year_Sold
##           -134650.92           -1061.43

##
## Call:
## lm(formula = Sale_Price ~ ., data = Ames_small)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -453124  -23174    -249    20696   324609
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    2.265e+06  1.240e+06   1.827  0.06780 .
## Gr_Liv_Area     7.769e+01  1.791e+00  43.383 < 2e-16 ***
## Central_AirY     4.095e+04  3.426e+03  11.953 < 2e-16 ***
## Kitchen_QualFair -1.443e+05  6.470e+03 -22.298 < 2e-16 ***
## Kitchen_QualGood -9.051e+04  3.430e+03 -26.386 < 2e-16 ***
## Kitchen_QualPoor -1.193e+05  4.423e+04  -2.697  0.00703 **
## Kitchen_QualTypical -1.347e+05  3.557e+03 -37.851 < 2e-16 ***
## Year_Sold       -1.061e+03  6.174e+02  -1.719  0.08570 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 43950 on 2922 degrees of freedom
## Multiple R-squared:  0.698, Adjusted R-squared:  0.6973
## F-statistic: 964.7 on 7 and 2922 DF, p-value: < 2.2e-16
```

Part 2

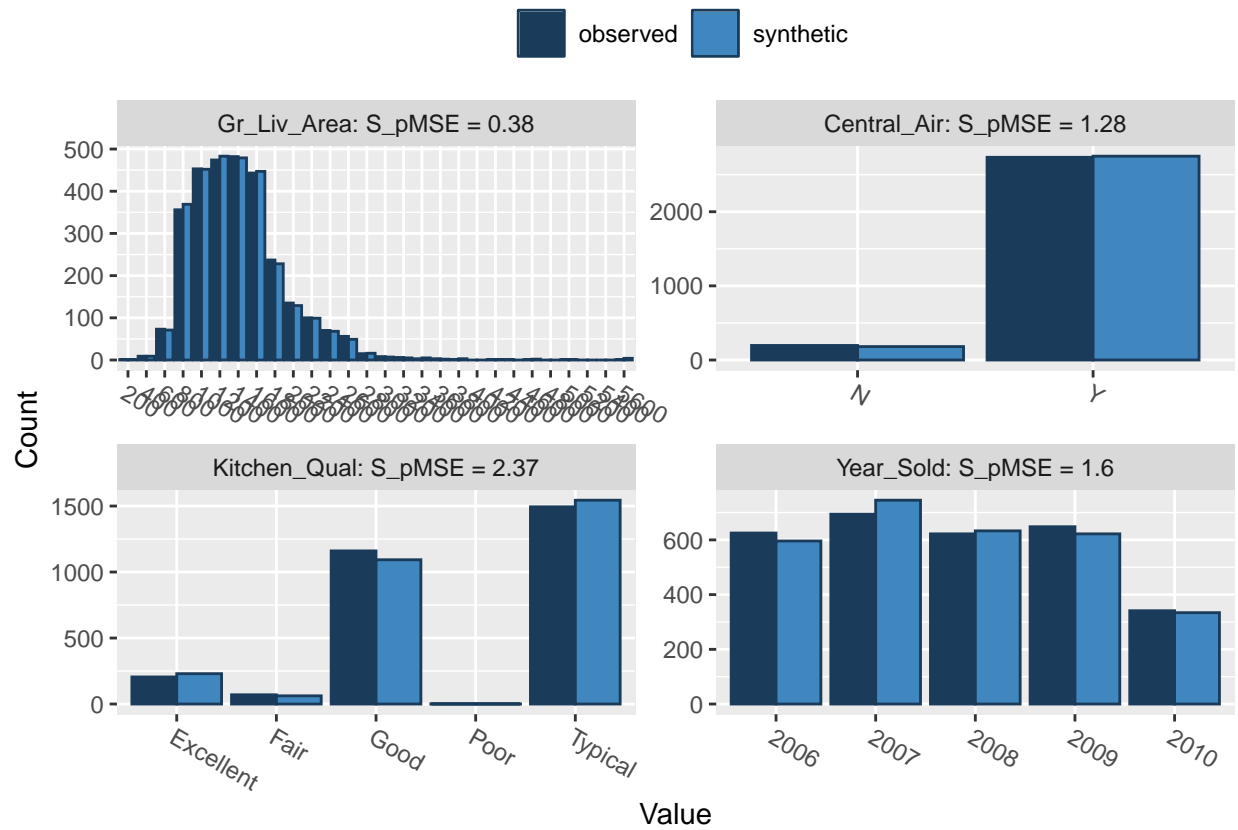
Now, use the `synthpop` package, perhaps including the “`syn`” and “`lm.synds`” commands to make a scatter plot and a synthetic linear model of `Ames_small`.

Discuss how it’s different than the original linear model, if at all.

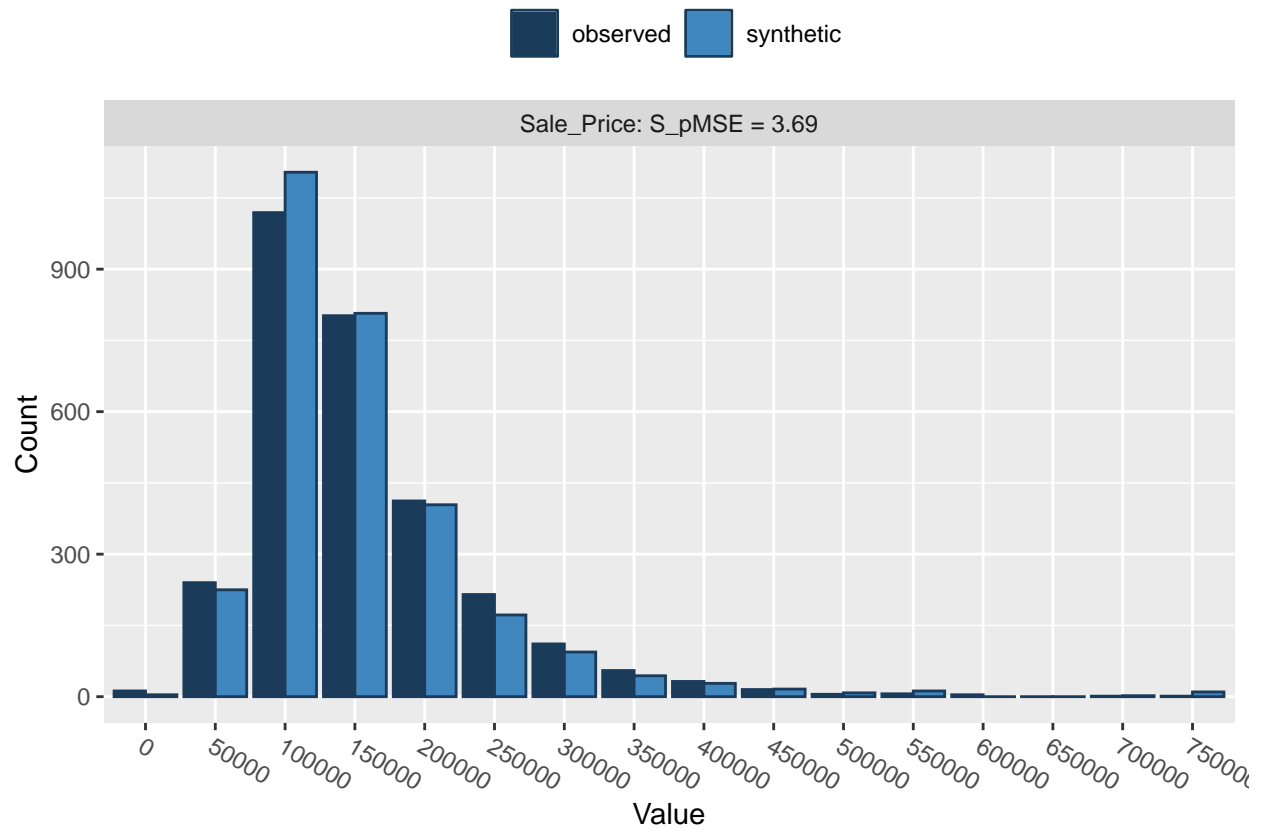
```
##
## Variable(s): Year_Sold numeric but with only 5 or fewer distinct values turned into factor(s) for syn
##
##
## Synthesis
## -----
##  Gr_Liv_Area Central_Air Kitchen_Qual Year_Sold Sale_Price

## Synthetic object with one synthesis using methods:
##  Gr_Liv_Area Central_Air Kitchen_Qual Year_Sold Sale_Price
##    "sample"    "logreg"    "polyreg"    "polyreg"    "normrank"
##
##  Gr_Liv_Area Central_Air Kitchen_Qual Year_Sold Sale_Price
##  Min.      : 334      N: 181      Excellent: 230  Min.      :2006  Min.      : 13100
##  1st Qu.:1123      Y:2749      Fair      : 62   1st Qu.:2007  1st Qu.:129500
##  Median :1436                Good      :1093  Median :2008  Median :157500
##  Mean   :1496                Poor      : 1   Mean   :2008  Mean   :179725
##  3rd Qu.:1729                Typical   :1544  3rd Qu.:2009  3rd Qu.:207000
##  Max.   :5642                Max.     :2010  Max.   :755000

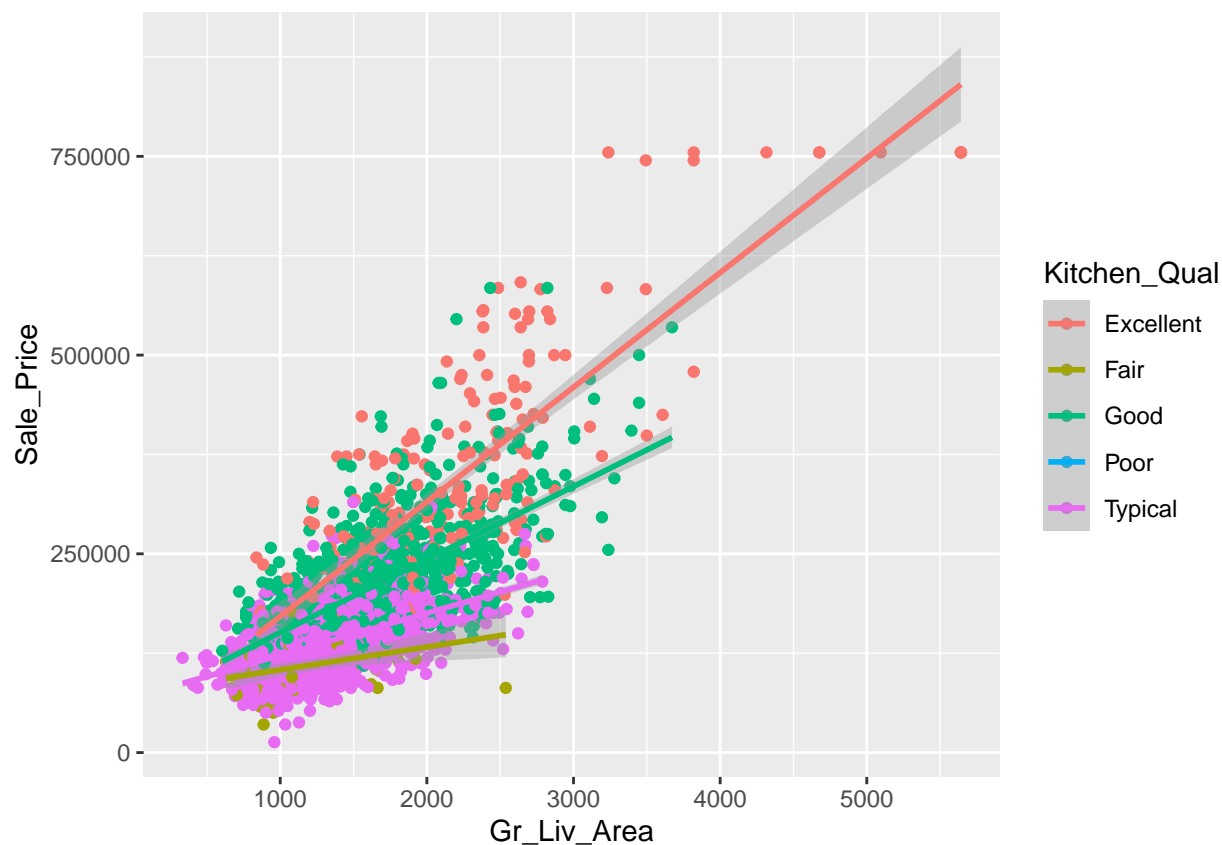
##
## Comparing counts observed with synthetic
```



Press return for next variable(s):



```
##
## Selected utility measures:
##      pMSE   S_pMSE df
## Gr_Liv_Area 0.000032 0.380693 4
## Central_Air 0.000027 1.275706 1
## Kitchen_Qual 0.000202 2.368497 4
## Year_Sold   0.000136 1.598788 4
## Sale_Price  0.000315 3.690517 4
```



```
##
## Call:
## lm.synds(formula = Sale_Price ~ ., data = Ames_small_syn)
##
## Coefficient estimates from a single synthesis:
##      (Intercept)      Gr_Liv_Area      Central_AirY      Kitchen_QualFair
##      3349312.87680         89.41704        38039.95928       -127069.72454
##      Kitchen_QualGood      Kitchen_QualPoor Kitchen_QualTypical      Year_Sold
##      -80393.10605       -165129.53058       -119493.42710       -1615.36733

## Fit to synthetic data set with a single synthesis. Inference to population
## coefficients when all variables in the model are synthesised.
##
## Call:
## lm.synds(formula = Sale_Price ~ ., data = Ames_small_syn)
##
## Combined estimates:
##      Beta.syn se.Beta.syn      z.syn Pr(>|z.syn|)
## (Intercept)  3.3493e+06  1.9053e+06   1.7579    0.07877 .
## Gr_Liv_Area   8.9417e+01  2.6562e+00  33.6633 < 2.2e-16 ***
## Central_AirY  3.8040e+04  5.2965e+03   7.1820  6.867e-13 ***
## Kitchen_QualFair -1.2707e+05  1.0039e+04 -12.6572 < 2.2e-16 ***
## Kitchen_QualGood -8.0393e+04  5.0259e+03 -15.9958 < 2.2e-16 ***
## Kitchen_QualPoor -1.6513e+05  6.6875e+04  -2.4692    0.01354 *
## Kitchen_QualTypical -1.1949e+05  5.1942e+03 -23.0050 < 2.2e-16 ***
```

```
## Year_Sold          -1.6154e+03  9.4899e+02  -1.7022      0.08872 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

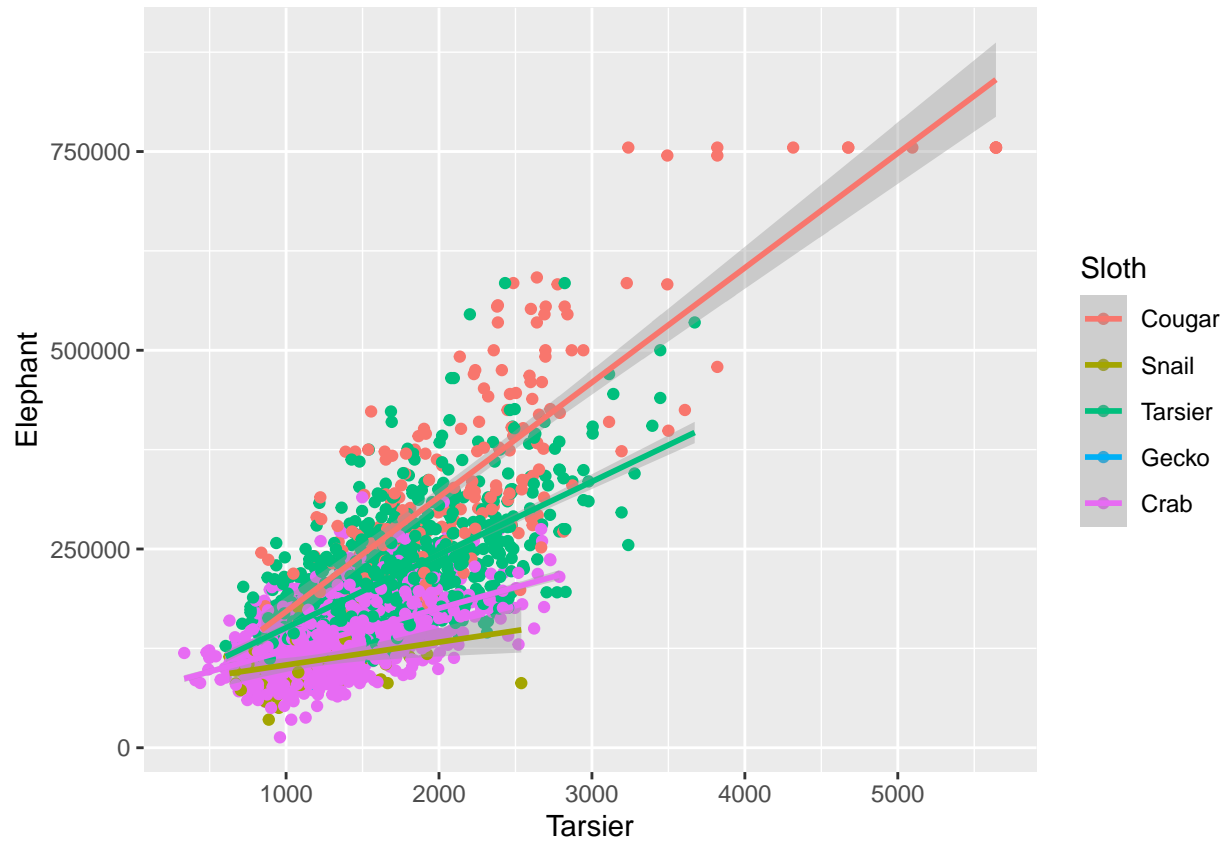
The seemingly significant difference between the original data and the synthesized data is the loss of “poor” kitchen quality. The word seemingly was purposely chosen as there was only one observation of “poor” kitchen quality in the original dataset so the loss of this category is actually a boon to the model.

It is hard to do an actual one-to-one comparison using the summary function due to the difference in the output. That being said, the coefficients are similar to one another as is the synthesized data to the original data so I feel comfortable stating that the two models performed similarly.

Part 3

Then, take a few minutes to check out another feature of synthpop (or another package) and explain what you found.

Implement it in a version of Ames_small and explain briefly what the feature does.



The synthpop package creates a simulated dataframe using parameters from the original data. Now there isn't anything particularly identifying about kitchen quality but I wanted to try the gganonymise function to see a new output.

Bonus

Not really sure what I'm doing here. Pretty much copy + paste from <https://github.com/brubinstein/diffpriv>
It has something to do with calculating theoretical sensitivity analysis

```
## a target function we'd like to run on private data X, releasing the result
target <- function(Ames_small_syn) mean(Ames_small_syn)

#install.packages("diffpriv")
library(diffpriv)
## target seeks to release a numeric, so we'll use the Laplace mechanism---a
## standard generic mechanism for privatizing numeric responses
mech <- DPMechLaplace(target = target)

## set a dataset sampling distribution, then estimate target sensitivity with
## sufficient samples for subsequent mechanism responses to achieve random
## differential privacy with confidence 1-gamma
distr <- function(n) rnorm(n)
mech <- sensitivitySampler(mech, oracle = distr, n = 5, gamma = 0.1)
#> Sampling sensitivity with m=285 gamma=0.1 k=285
mech@sensitivity    ## DPMech and subclasses are S4: slots accessed via @
```

```
## [1] 0.8101093
```

```
X <- c(0.328,-1.444,-0.511,0.154,-2.062) # length is sensitivitySampler() n
r <- releaseResponse(mech, privacyParams = DPParamsEps(epsilon = 1), X = X)
cat("Private response r$response:    ", r$response,
    "\nNon-private response target(X):", target(X))
```

```
## Private response r$response:    -0.4693441
## Non-private response target(X): -0.707
```