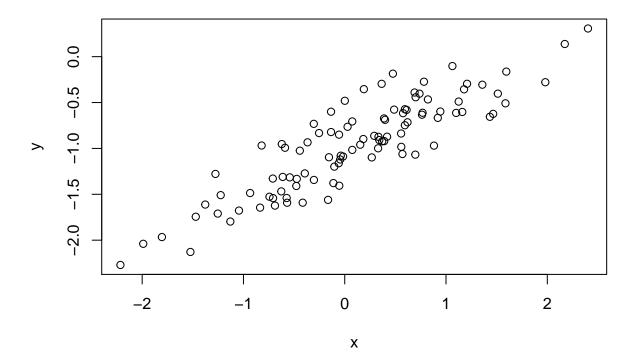
Linear Regression Simulation

Simulate data

```
set.seed(1)
windows(width=10, height=8)
x = rnorm(100)
eps = rnorm(100, 0, 0.25)
y = -1 + 0.5*x + eps
plot(x,y)
```

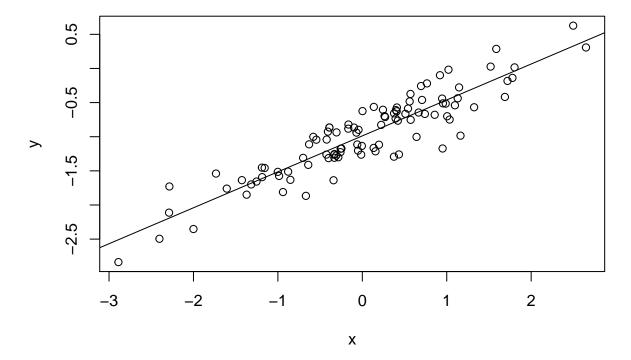


There is a linear relationship between x and y. They are positively correlated.

Predict y using x.

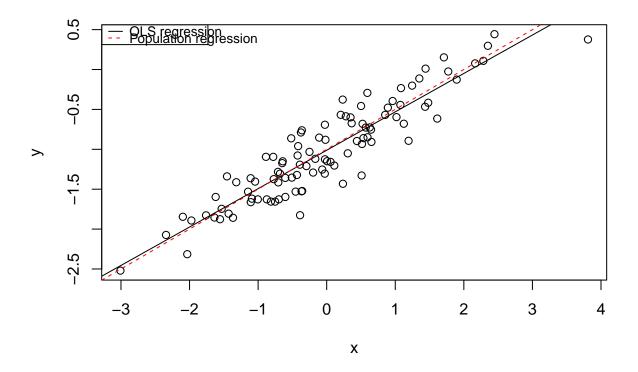
```
windows(width=10, height=8)
x = rnorm(100)
eps = rnorm(100, 0, 0.25)
y = -1 + 0.5*x + eps
plot(x,y)
```

```
fit1= lm(y~x)
abline(coef(fit1))
```



The beta estimates are very close to the actual parameter. However, beta 1 is statistically significantly different from 0.5.

Scatterplot:



Polynomial regression

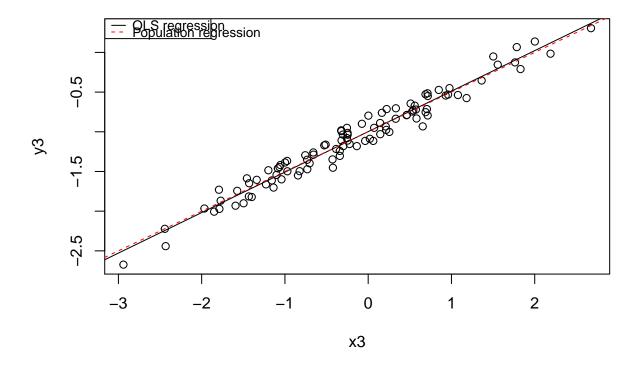
```
fit2= lm(y~x+I(x^2))
summary(fit2)
```

```
##
## Call:
## lm(formula = y ~ x + I(x^2))
##
## Residuals:
##
       Min
                  1Q
                       Median
                                    3Q
   -0.63403 -0.15501 0.00207 0.18784
##
##
## Coefficients:
                Estimate Std. Error t value Pr(>|t|)
##
                           0.029171 -34.407
## (Intercept) -1.003703
                                              <2e-16 ***
## x
                0.483237
                           0.021218
                                     22.775
                                              <2e-16 ***
               -0.005961
                           0.011809
                                    -0.505
                                               0.615
## I(x^2)
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2427 on 97 degrees of freedom
## Multiple R-squared: 0.846, Adjusted R-squared: 0.8428
## F-statistic: 266.4 on 2 and 97 DF, p-value: < 2.2e-16
```

It does not help because the R-squared decreases.

Less noise approach:

```
windows(width=10, height=8)
x3 = rnorm(100)
eps= rnorm(100, 0, 0.1)
y3 = -1 + 0.5*x3 + eps
plot(x3,y3)
fit3= lm(y3~x3)
summary(fit3)
##
## Call:
## lm(formula = y3 ~ x3)
## Residuals:
        Min
                1Q
                       Median
## -0.268223 -0.088552 -0.007682 0.092975 0.200080
##
## Coefficients:
            Estimate Std. Error t value Pr(>|t|)
## x3
             0.51005
                      0.01021 49.98 <2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.1097 on 98 degrees of freedom
## Multiple R-squared: 0.9622, Adjusted R-squared: 0.9619
## F-statistic: 2498 on 1 and 98 DF, p-value: < 2.2e-16
abline(coef(fit3))
abline(-1,0.5,col = 'red',lty = 2)
legend('topleft',
      legend = c("OLS regression", "Population regression"),
      col = c('black', 'red'),
      lty = 1:2, cex = 0.8,
)
```

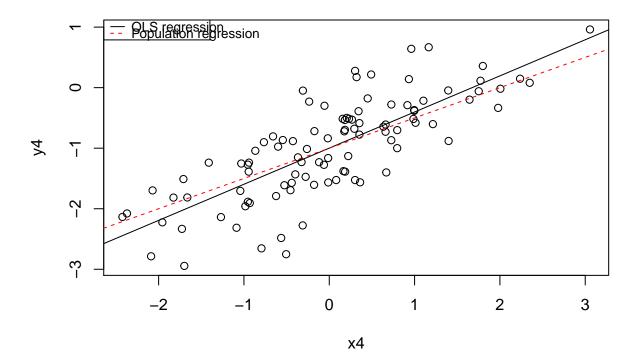


The estimated and actual regression line is almost identical.

More noise approach:

```
windows(width=10, height=8)
x4 = rnorm(100)
eps = rnorm(100, 0, 0.5)
y4 = -1 + 0.5*x4 + eps
plot(x4,y4)
fit4= lm(y4~x4)
summary(fit4)
###
```

```
## Call:
## lm(formula = y4 ~ x4)
##
## Residuals:
##
                  1Q
                      Median
  -1.45071 -0.31817 0.01701 0.34848 1.13426
##
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.99894
                           0.05195
                                   -19.23
                                             <2e-16 ***
## x4
                0.59663
                           0.04797
                                     12.44
                                             <2e-16 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
```



The estimates are less accurate because they have lower t value. The R-squared is lower.

0.4897954 0.5302986

x3

confint(fit4)

```
## 2.5 % 97.5 %
## (Intercept) -1.1020276 -0.8958549
## x4 0.5014353 0.6918155
```

The width of confidence interval with noisier data is higher.