lab 1

Yunting Chiu

2021-01-21

Example 1: US population

```r
# read dataset
library(tidyverse)
```

```
## -- Attaching packages ------------------------ tidyverse 1.3.0 --
```

```
## v ggplot2 3.3.2     v purrr   0.3.4
## v tibble  3.0.3     v dplyr   1.0.2
## v tidyr   1.1.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
```

```
## -- Conflicts --------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

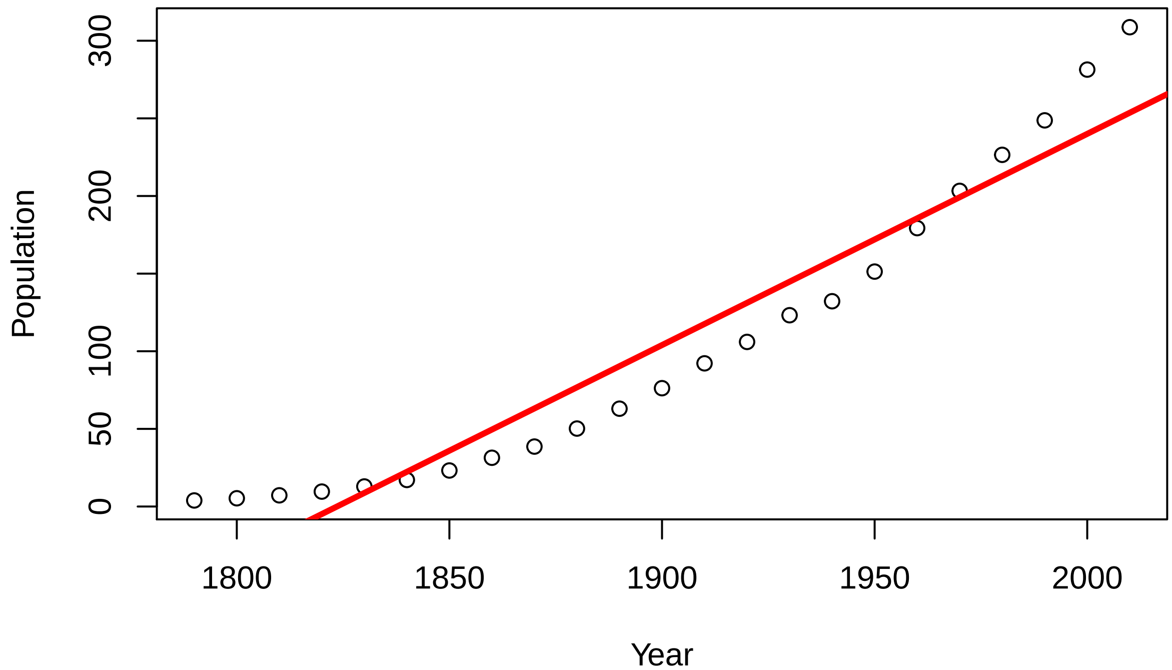
```r
USpop <- read_csv("./data/USpop.csv")
```

```
## Parsed with column specification:
## cols(
##   Year = col_double(),
##   Population = col_double()
## )
```

```r
USpop
```

```
## # A tibble: 23 x 2
##     Year Population
##    <dbl>      <dbl>
##  1  1790        3.9
##  2  1800        5.3
##  3  1810        7.2
##  4  1820        9.6
##  5  1830       12.9
##  6  1840       17.1
##  7  1850       23.2
##  8  1860       31.4
##  9  1870       38.6
## 10  1880       50.2
## # ... with 13 more rows
```

```r
attach(USpop) #replace %>%
plot(Year,Population)
regr = lm(Population ~ Year) # lm(y~x)
abline(regr, col="red", lwd=3) #fit a linear regression line
```



- According to the above plot, some outliers can be found at the right top, these observations can be defined as potential outliers, and the population does not grow linearly. We are therefore considering changing another model for this study case.

```
predict(regr, data.frame(Year=2020))
```

```
##        1
## 267.2166
```

```
summary(regr)
```

```
##
## Call:
## lm(formula = Population ~ Year)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -27.774 -24.872  -6.295  18.374  55.087
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.481e+03  1.672e+02  -14.84 1.33e-12 ***
## Year         1.360e+00  8.794e-02   15.47 5.93e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27.97 on 21 degrees of freedom
## Multiple R-squared:  0.9193, Adjusted R-squared:  0.9155
## F-statistic: 239.3 on 1 and 21 DF,  p-value: 5.927e-13
```

- With a small p-value, the summary of current simple linear model is indicates intercept and slope (Year) are reject the null hypothesis. Also, the Multiple R-squared is 91.93 % of the total variation (greater than 50 %). If we only focus on the result of R-squared, which is a good model, but the prerequisite is that we need to check the plot of x and y variables whether they are linear.

quadratic model

- We consider changing a `Year` variable to the quadratic transformation. That is, we need a quadratic term in our model.

```
quad <- lm(Population ~ poly(Year,2))
summary(quad)
```

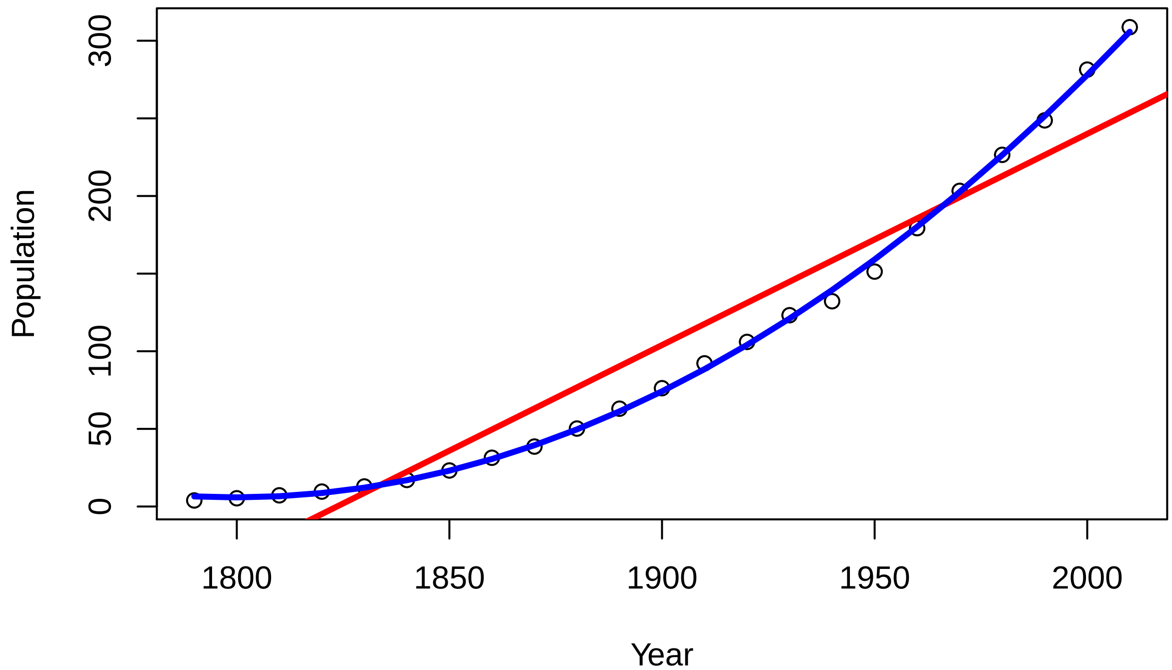
```
##
## Call:
## lm(formula = Population ~ poly(Year, 2))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.8220 -0.7130  0.5961  1.8344  3.7487
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    103.9739     0.6304  164.94   <2e-16 ***
## poly(Year, 2)1 432.7557     3.0231  143.15   <2e-16 ***
## poly(Year, 2)2 127.4790     3.0231   42.17   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.023 on 20 degrees of freedom
## Multiple R-squared:  0.9991, Adjusted R-squared:  0.999
## F-statistic: 1.113e+04 on 2 and 20 DF,  p-value: < 2.2e-16
```

```
Yhat <- predict(quad)

# recall and compare it
attach(USpop)
```

```
## The following objects are masked from USpop (pos = 3):
##
##     Population, Year
```

```
plot(Year,Population)
abline(regr, col="red", lwd = 3) #fit a linear regression line
lines(Year, Yhat, col = "blue", lwd = 3)
```



Firstly, we saw 99.9% of the total variation in this model. Secondly, The **Yhat** is quadratic polynomial of the **Year** from 1790 to 2010. Based on the plot above, it is obvious that the blue curve fits the data points better, meaning that the quadratic model predicts the US population better than the linear model.

```
predict(quad, data.frame(Year=c(2020,2030,2040)))
```

```
##        1        2        3
## 334.9518 365.4891 397.3812
```

Example 2

```
pres <- read_csv("./data/presidents.csv")
```

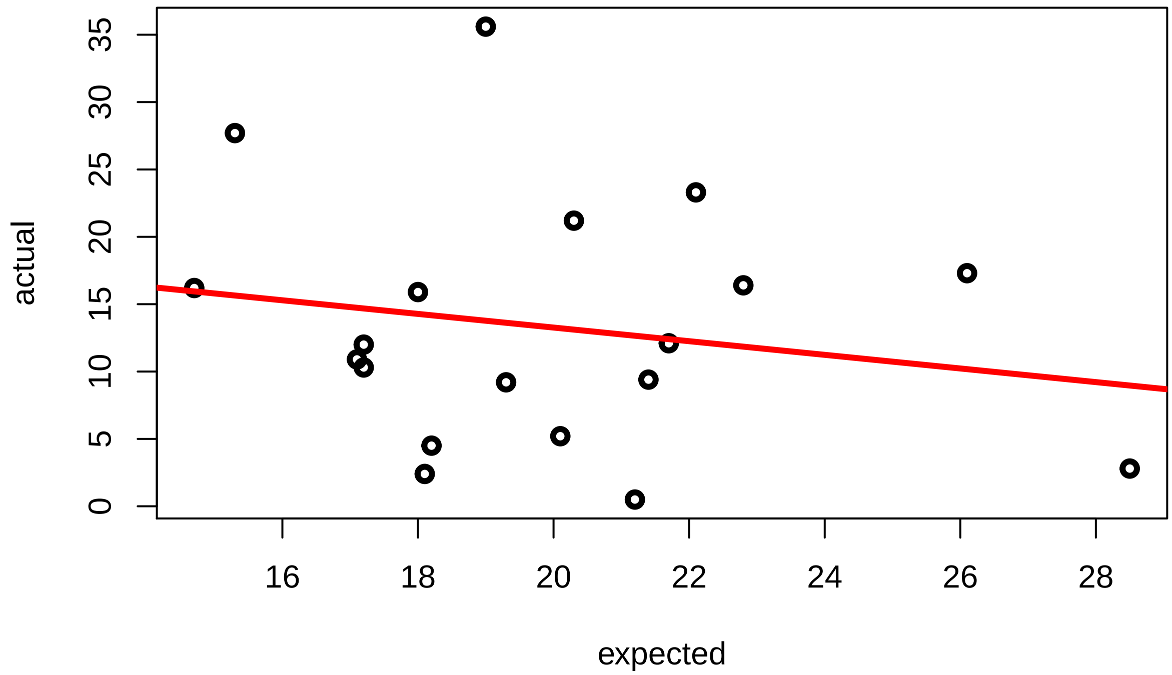
```
## Parsed with column specification:
## cols(
##   name = col_character(),
##   expected = col_double(),
##   actual = col_double()
## )
```

```
pres
```

```
## # A tibble: 19 x 3
##    name                  expected actual
##    <chr>                    <dbl>  <dbl>
##  1 ANDREW JOHNSON            17.2   10.3
##  2 ULYSSES S. GRANT          22.8   16.4
##  3 RUTHERFORD B. HAYES       18     15.9
##  4 JAMES A. GARFIELD         21.2    0.5
##  5 CHESTER A. ARTHUR         20.1    5.2
##  6 GROVER CLEVELAND          22.1   23.3
##  7 BENJAMIN HARRISON         17.2   12
##  8 WILLIAM MCKINLEY          18.2    4.5
##  9 THEODORE ROOSEVELT        26.1   17.3
```

```
## 10 WILLIAM H. TAFT           20.3   21.2
## 11 WOODROW WILSON            17.1   10.9
## 12 WARREN G. HARDING         18.1    2.4
## 13 CALVIN COOLIDGE           21.4    9.4
## 14 HERBERT C. HOOVER         19     35.6
## 15 FRANKLIN D. ROOSEVELT     21.7   12.1
## 16 HARRY S. TRUMAN           15.3   27.7
## 17 DWIGHT D. EISENHOWER      14.7   16.2
## 18 JOHN F. KENNEDY           28.5    2.8
## 19 LYNDON B. JOHNSON         19.3    9.2
```

```r
attach(pres)
plot(expected, actual, lwd=3)
reg = lm(actual ~ expected)
abline(reg, col="red", lwd=3)
```




```r
Z = c(4,8,18)
reg = lm(actual ~ expected, data=pres[-Z,])
summary(reg)
```

```
##
## Call:
## lm(formula = actual ~ expected, data = pres[-Z, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -12.923  -5.248  -1.317   2.974  20.280
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 15.384876  14.970195   1.028    0.322
## expected    -0.003409   0.763337  -0.004    0.997
##
```

```
## Residual standard error: 8.771 on 14 degrees of freedom
## Multiple R-squared:  1.424e-06,  Adjusted R-squared:  -0.07143
## F-statistic: 1.994e-05 on 1 and 14 DF,  p-value: 0.9965
```