R regression analysis

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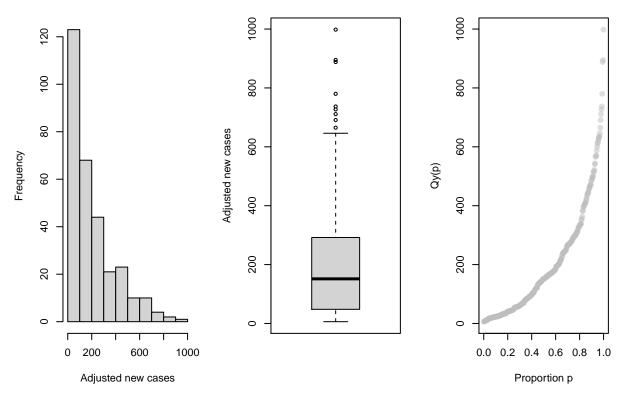
2021/4/11

#R regression analysis ## we use the Covid-19 daily new cases of Toronto from March 2020 to December 2020. The data source can be found at https://raw.githubusercontent.com/kentranz/socialMobilityCOVID/master/data/raw/TorontoCovid.toronto.covid

```
## 2
       3/2/20
                      2
                                 7
## 3
       3/3/20
                      3
                                12
## 4
       3/4/20
                      4
                                 9
## 5
       3/5/20
                      5
                                10
                      6
## 6
       3/6/20
                                11
## 7
       3/7/20
                      7
                                 9
## 8
       3/8/20
                      8
                                10
                     9
## 9
       3/9/20
                                25
## 10 3/10/20
                     10
                                31
## 11 3/11/20
                                32
                     11
## 12 3/12/20
                     12
                                45
## 13 3/13/20
                     13
                                54
## 14 3/14/20
                     14
                                61
## 15 3/15/20
                                57
                     15
```

main = "Quantile plot of adjusted new cases")

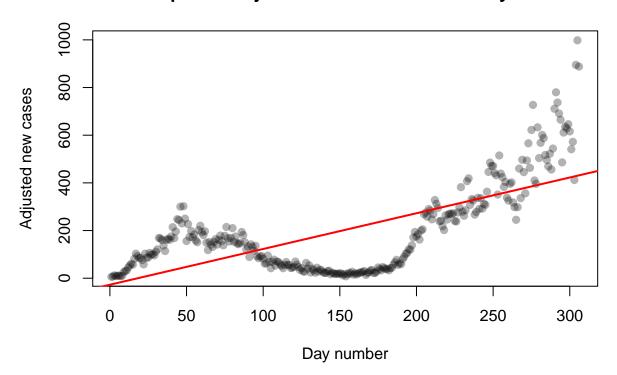
Histogram of adjusted new case Boxplot of adjusted new case: Quantile plot of adjusted new ca



(c)

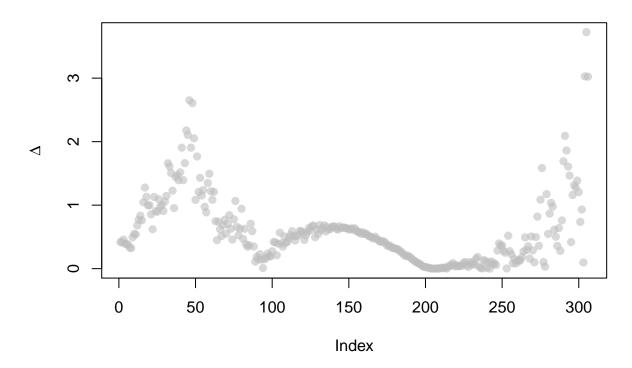
```
plot(tor$Day_Num, tor$New_Cases, main = "Scatterplot of adjusted new cases versus day number", pch = 19
     xlab = "Day number",
     ylab = "Adjusted new cases")
fit = lm(New_Cases~Day_Num, data=tor)
abline(fit, col="red", lwd=2)
```

Scatterplot of adjusted new cases versus day number



```
N = nrow(tor)
delta = matrix(0, nrow = N, ncol = 2)
for(i in 1:N) {
   fit.no.i = lm(New_Cases ~ Day_Num, data = tor[-i,])
   delta[i, ] = abs(fit$coef - fit.no.i$coef)
}
delta2 = apply(X = delta, MARGIN = 1, FUN =function(z) {
   sqrt(sum(z^2))})
plot(delta2, main = bquote("The Influence of each observation on regression parameter" ~ theta), ylab =
   col = adjustcolor("grey", 0.6))
```

The Influence of each observation on regression parameter θ



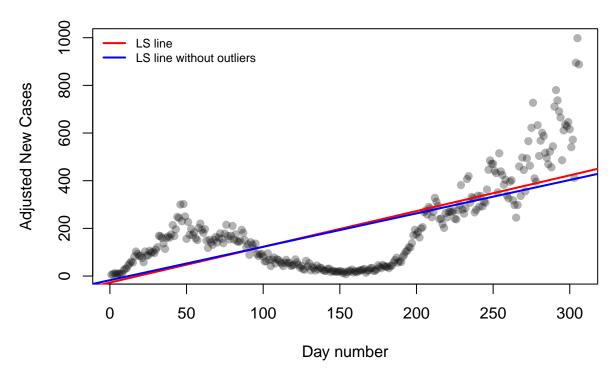
We are going to find the three most influential observations from the population

```
tor$Date[delta2>=sort(delta2, decreasing = TRUE)[3]]
```

```
## [1] "12/29/20" "12/30/20" "12/31/20"
```

Then we are going to remove the three most influential observations from the population and calculate the least squares regression line using the observations that remain.

Scatterplot of adjusted New Cases versus day number



Instead of removing highly influential observations, we could perform a robust linear regression to mitigate their influence. In addition, we use Turkey's bisquare objective function in the robust linear regression.

$$\rho_k(r) = \begin{cases} \frac{r^2}{2} - \frac{r^4}{2k^2} + \frac{r^6}{6k^4} & \text{for } |r| \le k \\ \frac{k^2}{6} & \text{for } |r| > k \end{cases}$$

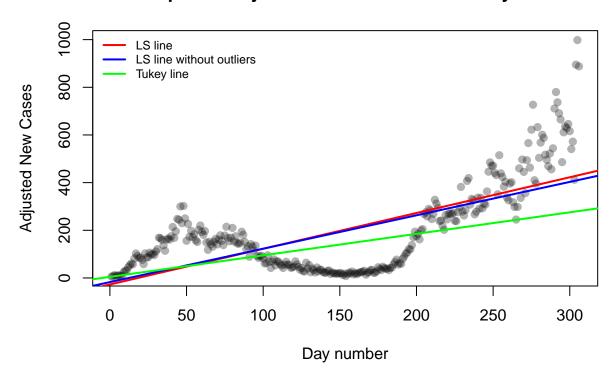
The above is the Turkey Bisquare objective function we are going to use.

```
tukey.fn <- function(r, k) {
  val = (r^2)/2 - (r^4)/(2*k^2) + (r^6)/(6*k^4)
  subr = abs(r) > k
  val[ subr ] = (k^2)/6
  return(val)
}
tukey.fn.prime <- function(r, k) {
  val = r - (2*r^3)/(k^2) + (r^5)/(k^4)
  subr = abs(r) > k
  val[ subr ] = 0
  return(val)
}
```

```
createRobustTukeyRho <- function(x, y, kval) {
  function(theta) {
    alpha <- theta[1]
    beta <- theta[2]
    sum(tukey.fn(y - alpha - beta * x, k = kval))</pre>
```

```
}
createRobustTukeyGradient <- function(x, y, kval) {</pre>
    function(theta) {
        alpha <- theta[1]</pre>
        beta <- theta[2]
        ru = y - alpha - beta * x
        rhok = tukey.fn.prime(ru, k = kval)
        -1 * c(sum(rhok * 1), sum(rhok * x))
    }
}
Then, we are going to use k = 6
rho <- createRobustTukeyRho(x=tor$Day_Num, y=tor$New_Cases, k=6)</pre>
gradient <- createRobustTukeyGradient(x=tor$Day_Num, y=tor$New_Cases, k=6)
result <- nlminb(start = c(0,1), objective = rho, gradient = gradient)
result
## $par
## [1] 4.6124967 0.9027154
##
## $objective
## [1] 1759.225
## $convergence
## [1] 0
##
## $iterations
## [1] 8
## $evaluations
## function gradient
##
         21
##
## $message
## [1] "relative convergence (4)"
plot(tor$Day_Num, tor$New_Cases, main = "Scatterplot of adjusted New Cases versus day number", pch = 19
     xlab = "Day number",
     ylab = "Adjusted New Cases")
abline(fit, col="red", lwd=2)
index = which(delta2>=sort(delta2, decreasing = TRUE)[3])
w = rep(1, N)
w[index] = 0
fit2 = lm(New_Cases~Day_Num, weights = w, data = tor)
abline(fit2, col="blue", lwd=2)
abline(result$par, col="green", lwd=2)
```

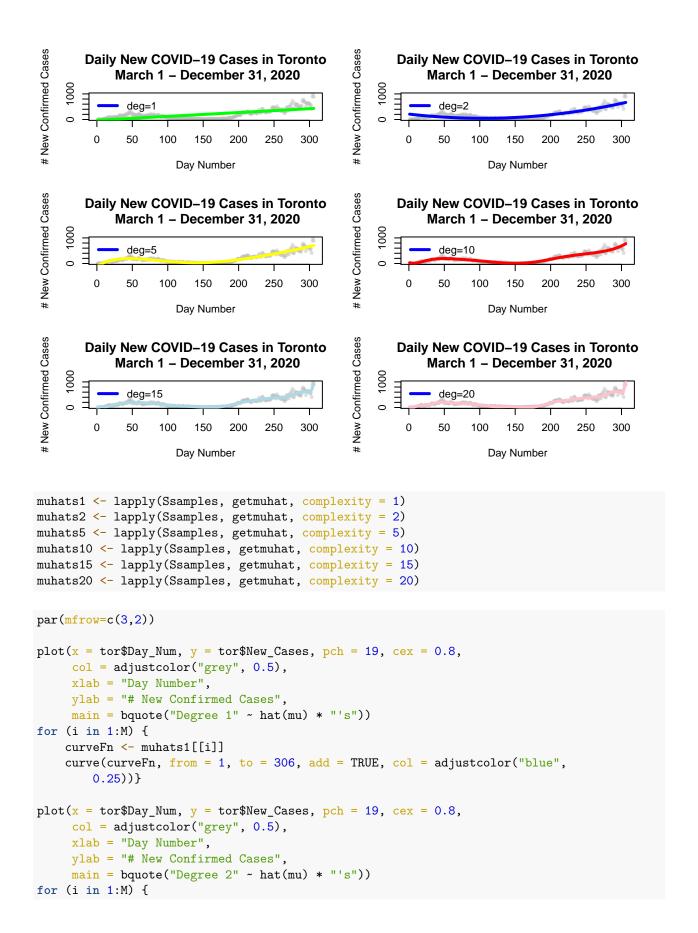
Scatterplot of adjusted New Cases versus day number



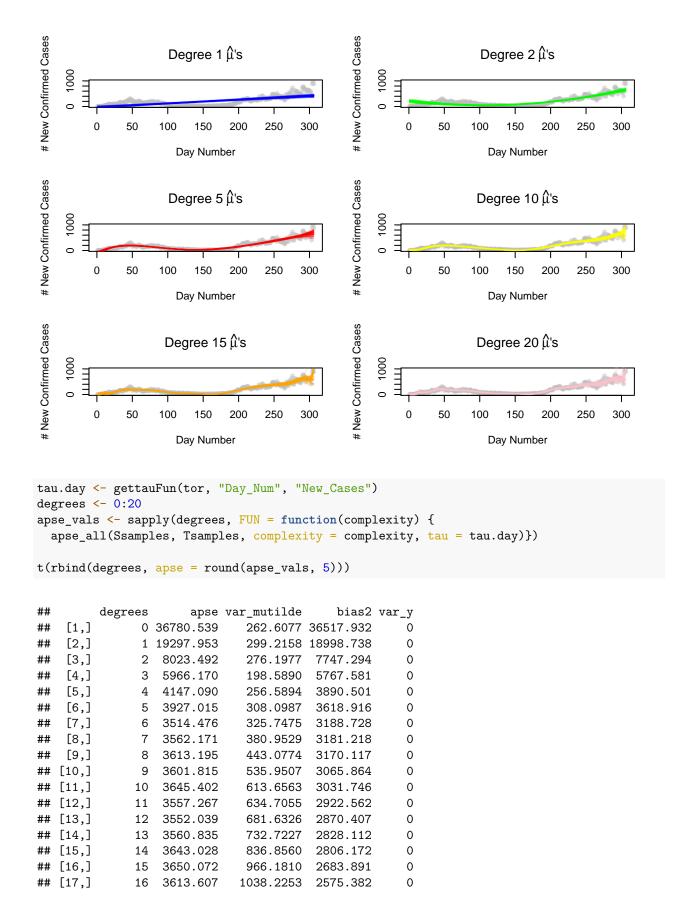
By observing the three linear regression line, we can see that the turkey line(green one) is less affected by the outliers.

Next, we are going to use polynomials to model the covid-19 data.

```
muhat2 <- getmuhat(data.frame(x = tor$Day_Num, y = tor$New_Cases), 2)</pre>
curve(muhat2, from = 1, to = 306, add = TRUE, col = "blue", lwd = 3)
legend("topleft", legend = "deg=2", col = "blue", lwd = 3, bty = "n")
plot(x = tor$Day_Num, y = tor$New_Cases, pch=16, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = "Daily New COVID-19 Cases in Toronto\n March 1 - December 31, 2020")
muhat5 <- getmuhat(data.frame(x = tor$Day_Num, y = tor$New_Cases), 5)</pre>
curve(muhat5, from = 1, to = 306, add = TRUE, col = "yellow", lwd = 3)
legend("topleft", legend = "deg=5", col = "blue", lwd = 3, bty = "n")
plot(x = tor$Day_Num, y = tor$New_Cases, pch=16, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = "Daily New COVID-19 Cases in Toronto\n March 1 - December 31, 2020")
muhat10 <- getmuhat(data.frame(x = tor$Day_Num, y = tor$New_Cases), 10)</pre>
curve(muhat10, from = 1, to = 306, add = TRUE, col = "red", lwd = 3)
legend("topleft", legend = "deg=10", col = "blue", lwd = 3, bty = "n")
plot(x = tor$Day_Num, y = tor$New_Cases, pch=16, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = "Daily New COVID-19 Cases in Toronto\n March 1 - December 31, 2020")
muhat15 <- getmuhat(data.frame(x = tor$Day_Num, y = tor$New_Cases), 15)</pre>
curve(muhat15, from = 1, to = 306, add = TRUE, col = "lightblue", lwd = 3)
legend("topleft", legend = "deg=15", col = "blue", lwd = 3, bty = "n")
plot(x = tor$Day_Num, y = tor$New_Cases, pch=16, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = "Daily New COVID-19 Cases in Toronto\n March 1 - December 31, 2020")
muhat20 <- getmuhat(data.frame(x = tor$Day_Num, y = tor$New_Cases), 20)</pre>
curve(muhat20, from = 1, to = 306, add = TRUE, col = "pink", lwd = 3)
legend("topleft", legend = "deg=20", col = "blue", lwd = 3, bty = "n")
```



```
curveFn <- muhats2[[i]]</pre>
    curve(curveFn, from = 1, to = 306, add = TRUE, col = adjustcolor("green",
        0.25))
plot(x = tor$Day_Num, y = tor$New_Cases, pch = 19, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = bquote("Degree 5" ~ hat(mu) * "'s"))
for (i in 1:M) {
    curveFn <- muhats5[[i]]</pre>
    curve(curveFn, from = 1, to = 306, add = TRUE, col = adjustcolor("red",
        0.25))
plot(x = tor$Day_Num, y = tor$New_Cases, pch = 19, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = bquote("Degree 10" ~ hat(mu) * "'s"))
for (i in 1:M) {
    curveFn <- muhats10[[i]]</pre>
    curve(curveFn, from = 1, to = 306, add = TRUE, col = adjustcolor("yellow",
plot(x = tor$Day_Num, y = tor$New_Cases, pch = 19, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = bquote("Degree 15" ~ hat(mu) * "'s"))
for (i in 1:M) {
    curveFn <- muhats15[[i]]</pre>
    curve(curveFn, from = 1, to = 306, add = TRUE, col = adjustcolor("orange",
        0.25))
plot(x = tor$Day_Num, y = tor$New_Cases, pch = 19, cex = 0.8,
     col = adjustcolor("grey", 0.5),
     xlab = "Day Number",
     ylab = "# New Confirmed Cases",
     main = bquote("Degree 20" ~ hat(mu) * "'s"))
for (i in 1:M) {
    curveFn <- muhats20[[i]]</pre>
    curve(curveFn, from = 1, to = 306, add = TRUE, col = adjustcolor("pink",
        0.25))
```

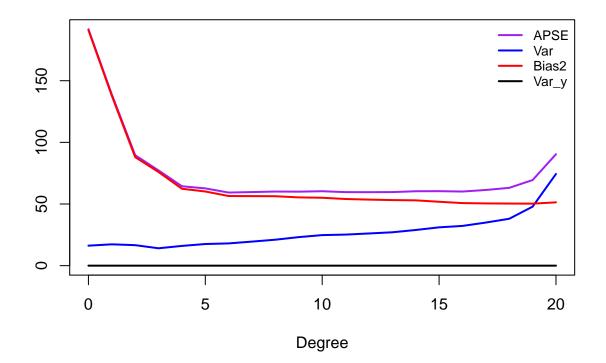


```
## [18,]
             17 3769.307
                            1221.5320 2547.775
## [19,]
             18 3981.631
                            1445.2355 2536.396
                                                    0
## [20,]
             19 4819.604
                            2289.9750 2529.629
                                                    0
## [21,]
                 8167.623
                            5531.3125 2636.310
                                                    0
             20
plot(degrees, sqrt(apse_vals[1, ]), xlab = "Degree", ylab = "", type = "1",
    ylim = c(0, max(sqrt(apse_vals))), col = "purple", lwd = 2)
lines(degrees, sqrt(apse_vals[2, ]), col = "blue", lwd = 2)
lines(degrees, sqrt(apse_vals[3, ]), col = "red", lwd = 2)
```

legend("topright", legend = c("APSE", "Var", "Bias2", "Var_y"), col = c("purple",

lines(degrees, sqrt(apse_vals[4,]), col = "black", lwd = 2)

"blue", "red", "black"), lwd = 2, bty = "n", cex = 0.8)

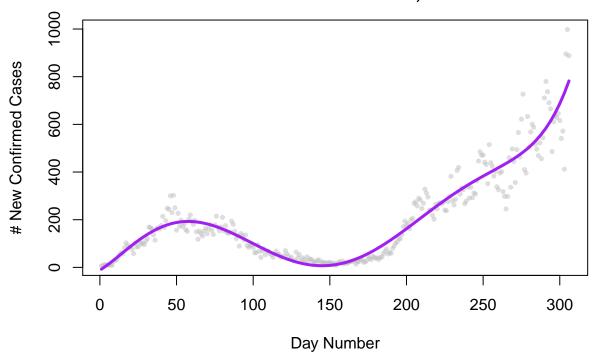


```
best.deg <- degrees[which.min(apse_vals[1, ])]
print(best.deg)</pre>
```

[1] 6

```
main = "Daily New COVID-19 Cases in Toronto\n March 1 - December 31, 2020")
curve(muhat.best, from = 1, to = 306, add = TRUE, col = "purple", lwd = 3)
```

Daily New COVID-19 Cases in Toronto March 1 – December 31, 2020

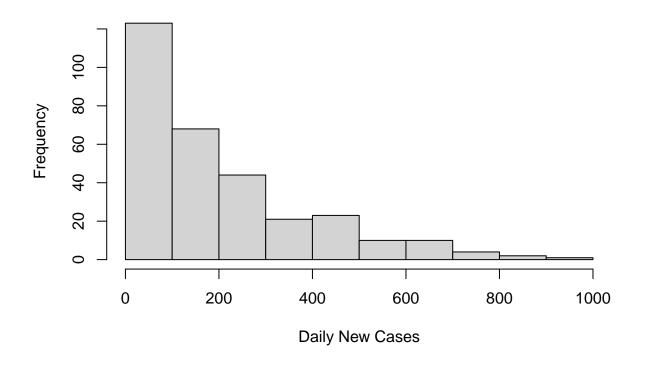


Thus, we find the best polynomial model with degree = 6.

Then, we are going to use gamma distribution as the potential model for the data and use Method of Moments estimation and Maximum Likelihood (ML) estimation to estimate the paramaters alpha and beta for the distribution.

hist(tor\$New_Cases, main = 'The Histogram of Daily New Cases', xlab = 'Daily New Cases')

The Histogram of Daily New Cases



```
beta.mm =(mean(tor$New_Cases^2)-(mean(tor$New_Cases))^2) / mean(tor$New_Cases)
alpha.mm = mean(tor$New_Cases) / beta.mm
c(alpha.mm, beta.mm)
```

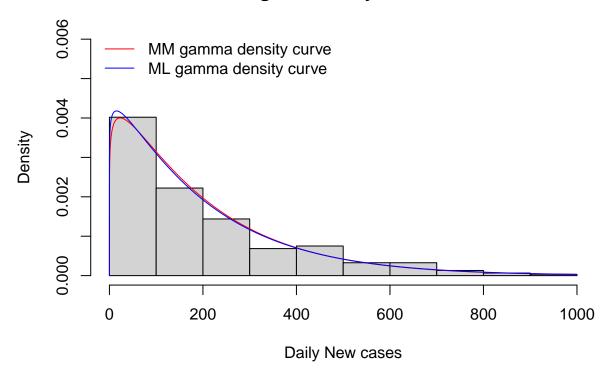
[1] 1.127008 179.989514

```
beta <- theta[2]</pre>
    c(-N* digamma(alpha) - N*log(beta) + sum(log(y)), -alpha*N/beta + sum(y)/beta^2)
  }
}
creatGammaPsiPrimeFn <- function(y){</pre>
  N <- length(y)
  function(theta){
    alpha = theta[1]
    beta = theta[2]
    mat = matrix(0, nrow=length(theta), ncol=length(theta))
    mat[1,1] = -N*trigamma(alpha)
    mat[1,2] = -N/beta
    mat[2,1] = -N/beta
    mat[2,2] = alpha*N/beta^2-2*sum(y)/beta^3
    return(mat)
}
psi <- createGammaPsifn(tor$New_Cases)</pre>
psiPrime <- creatGammaPsiPrimeFn(tor$New_Cases)</pre>
Result <- NewtonRaphson(theta = c(alpha.mm, beta.mm), psiFn = psi, psiPrimeFn = psiPrime)
print(Result)
## $theta
## [1]
         1.081193 187.616478
## $converged
## [1] TRUE
##
## $iteration
## [1] 4
## $fnValue
## [1] 0 0
alpha.ml = Result$theta[1]
beta.ml = Result$theta[2]
hist(tor$New_Cases, prob=TRUE, ylim = c(0, 0.006), main = 'Histogram of daily new cases', xlab = 'Daily
x = seq(0, 1000, 0.1)
lines(x, dgamma(x, shape = alpha.mm, scale = beta.mm), col='red')
lines(x, dgamma(x, shape = alpha.ml, scale = beta.ml), col='blue')
legend('topleft', \ legend = c('MM \ gamma \ density \ curve', \ 'ML \ gamma \ density \ curve'), \ col = c('red', 'blue'),
```

createGammaPsifn <- function(y){</pre>

N <- length(y)
function(theta){
 alpha <- theta[1]</pre>

Histogram of daily new cases



From the above plot, we can see that MM gamma density curve and ML gamma density curve is similar. And we can use the gamma model to describe the probability of the certain number of Covid-19 daily new cases of the future.

By comparison, we can clearly see that the polynomial model with degree 6 is better fitted to the data than linear regression model and linear robust regression model. Then we can use the polynomial model with degree 6 to predict the future Covid-19 daily new cases.