

# 短学期上机考试

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## 1 六

```
before = c(57, 54, 62, 64, 71, 65, 70, 75, 68, 70, 77, 74, 80, 83)
after = c(55, 60, 68, 69, 70, 73, 74, 74, 75, 76, 76, 78, 81, 90)
t.test(before, after, paired = TRUE)

##
## Paired t-test
##
## data: before and after
## t = -3.6927, df = 13, p-value = 0.002707
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -5.547628 -1.452372
## sample estimates:
## mean of the differences
## -3.5
```

由上述 t 检验结果可以看出, p 值为  $0.002707 < 0.05$ , 也就是拒绝原假设, 故 alcohol 对 reflexes 有效果。

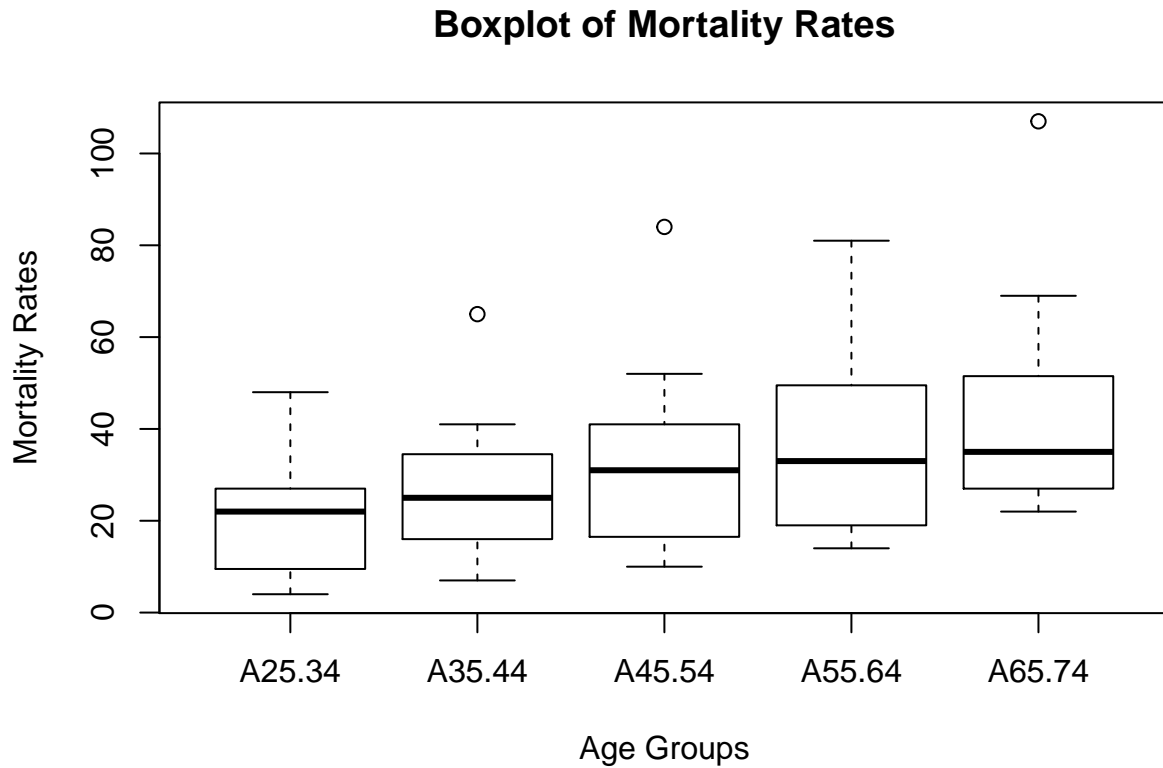
## 2 七

首先构造数据如下所示

```
A25.34 <- c(22, 9, 22, 29, 16, 28, 48, 7, 8, 26, 4, 28, 22, 10, 20)
A35.44 <- c(27, 19, 19, 40, 25, 35, 65, 8, 11, 29, 7, 41, 34, 13, 22)
A45.54 <- c(31, 10, 21, 52, 36, 41, 84, 11, 18, 36, 10, 46, 41, 15, 28)
A55.64 <- c(34, 14, 31, 53, 47, 49, 81, 18, 20, 32, 16, 51, 50, 17, 33)
A65.74 <- c(24, 27, 49, 69, 56, 52, 107, 27, 28, 28, 22, 35, 51, 22, 37)
df <- data.frame(A25.34, A35.44, A45.54, A55.64, A65.74)
rownames(df) <- c("Canada", "Israel", "Japan", "Austria", "France",
                  "Germany", "Hungary", "Italy", "Netherlands", "Poland",
                  "Spain", "Sweden", "Switzerland", "UK", "USA")
```

首先对数据框进行转换, 然后进一步绘出箱线图

```
df.stack = stack(df)
boxplot(values~ind, data = df.stack, main = "Boxplot of Mortality Rates",
        xlab = "Age Groups", ylab = "Mortality Rates")
```



从箱线图可以看出，不同年龄群的 Mortality Rates 有差异，其均值随着年龄的增长而增大。

## 3 八

### 3.1 (a)

重复  $n$  次实验，点  $(x_1, x_2)$  到最近边的距离小于 0.25 的个数为  $m_1$ ，则估计的概率为

$$p(\text{the distance between } (x_1, x_2) \text{ and the nearest edge}) = \frac{m_1}{n}$$

编写 `simPoints(n)` 函数返回生成的  $n$  个随机点。

```
simPoints <- function(n)
{
  x1 = runif(n)
  x2 = runif(n)
  return(data.frame(x1, x2))
}
```

编写 `isNearestPointToEdge(x)` 函数来判断输入的  $x$  点是否离最近边的距离小于 0.25，若是，则返回 TRUE，否则返回 FALSE。

```
isNearestPointToEdge <- function(x)
{
  # 点 x 到四条边的距离
  dist = sapply(x, function(y) c(y, 1-y))
  # 点 x 到四条边最近的距离
  dist.min = min(dist)
  # 若小于 0.25, 返回 TRUE
  if (dist.min < 0.25)
    return(TRUE)
  else
    return(FALSE)
}
```

统计满足条件的点的个数

```
n = 1000
x <- simPoints(n)
x.near.edge <- apply(x, 1, function(y) isNearestPointToEdge(y))
m1 = sum(x.near.edge)
```

则概率为

```
m1/n
```

```
## [1] 0.736
```

### 3.2 (b)

重复  $n$  次实验, 点  $(x_1, x_2)$  到最近点的距离小于 0.25 的个数为  $m_2$ , 则估计的概率为

$$p(\text{the distance between } (x_1, x_2) \text{ and the nearest vertex}) = \frac{m_2}{n}$$

编写函数 isNearestPointToVertex(x), 判断该点是否离最近顶点的距离小于 0.25, 若是, 则返回 TRUE, 否则返回 FALSE。

```
isNearestPointToVertex <- function(x)
{
  # 点 x 到四个顶点的距离
  dist = c(sqrt(x[1]^2+x[2]^2),
           sqrt((x[1]-1)^2+x[2]^2),
           sqrt(x[1]^2+(x[2]-1)^2),
           sqrt((x[1]-1)^2+(x[2]-1)^2))
  # 点 x 到四个顶点最近的距离
  dist.min = min(dist)
  # 若小于 0.25, 返回 TRUE
```

```

    if (dist.min < 0.25)
      return(TRUE)
    else
      return(FALSE)
  }

```

统计满足条件的点的个数

```

x.near.vertex <- apply(x, 1, function(y) isNearestPointToVertex(y))
m2 = sum(x.near.vertex)

```

则概率为

$m2/n$

```
## [1] 0.192
```

## 4 九

### 4.1 (a)

```
ChickWeight.split = with(ChickWeight, split(ChickWeight, Chick))
```

提取出 Chick 为 34 的数据

```

ChickWeight.chick34 <- ChickWeight.split$`34`
ChickWeight.chick34

```

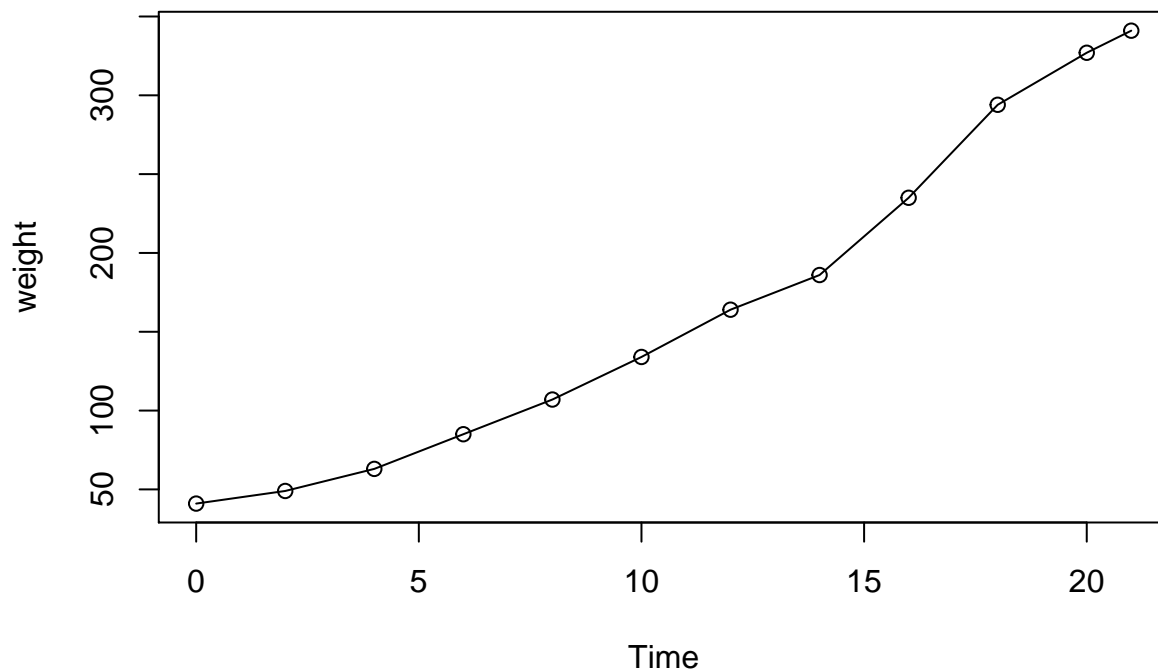
```

##      weight Time Chick Diet
## 377      41    0    34    3
## 378      49    2    34    3
## 379      63    4    34    3
## 380      85    6    34    3
## 381     107    8    34    3
## 382     134   10    34    3
## 383     164   12    34    3
## 384     186   14    34    3
## 385     235   16    34    3
## 386     294   18    34    3
## 387     327   20    34    3
## 388     341   21    34    3

```

然后作图

```
plot(weight ~ Time, data = ChickWeight.chick34, type = "o")
```



## 4.2 (b)

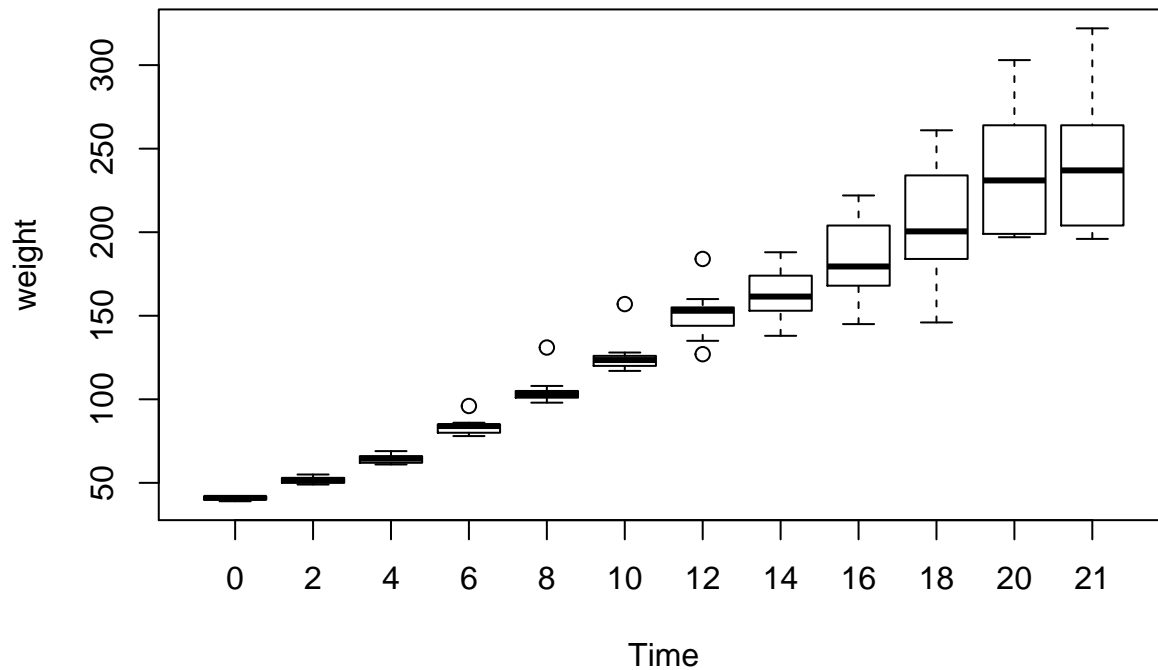
首先提取出 diet group 为 4 的数据

```
ChickWeight.split.diet = with(ChickWeight, split(ChickWeight, Diet))
ChickWeight.diet4 <- ChickWeight.split.diet$`4`
head(ChickWeight.diet4)
```

```
##      weight Time Chick Diet
## 461      42    0    41    4
## 462      51    2    41    4
## 463      66    4    41    4
## 464      85    6    41    4
## 465     103    8    41    4
## 466     124   10    41    4
```

```
boxplot(weight ~ Time, data = ChickWeight.diet4,
        xlab = "Time", ylab = "weight", main = "Boxplot for Diet Group 4")
```

### Boxplot for Diet Group 4



#### 4.3 (c)

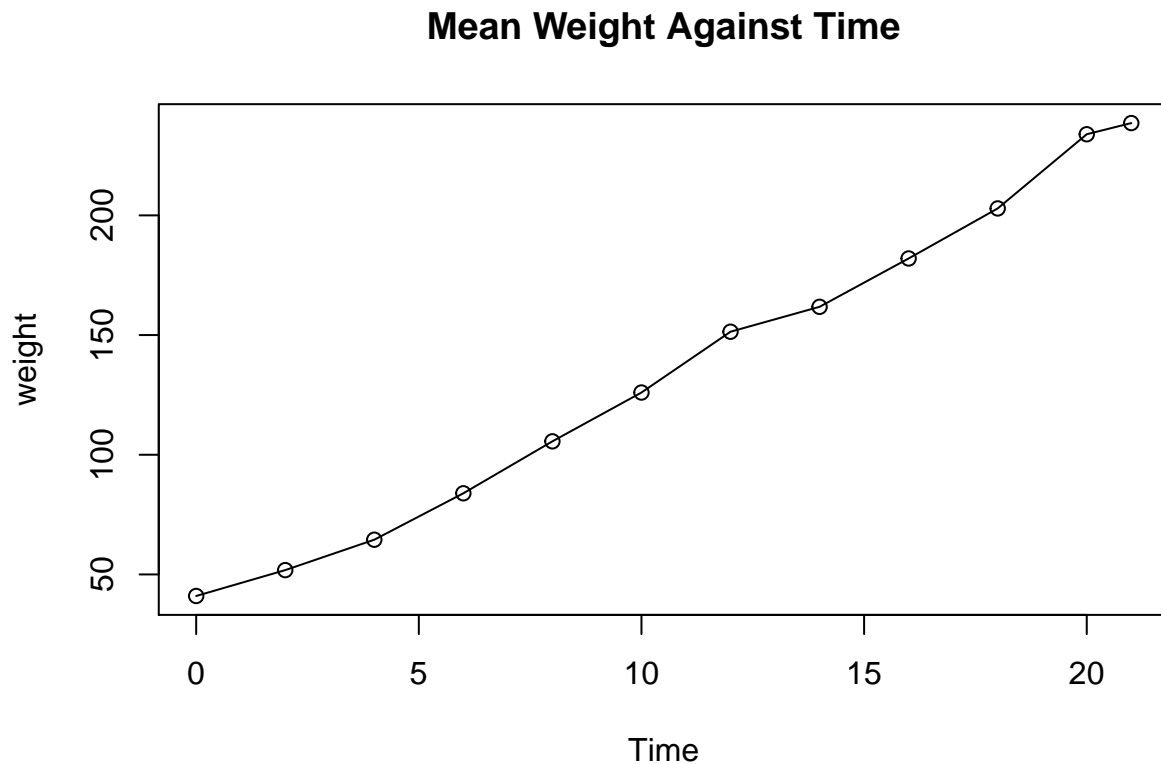
计算每个时间点 weight 的均值

```
ChickWeight.diet4.mean <- with(ChickWeight.diet4,  
                                aggregate(weight, by = list(Time), mean))  
colnames(ChickWeight.diet4.mean) <- c("Time", "weight")  
ChickWeight.diet4.mean
```

```
##      Time  weight  
## 1      0  41.0000  
## 2      2  51.8000  
## 3      4  64.5000  
## 4      6  83.9000  
## 5      8 105.6000  
## 6     10 126.0000  
## 7     12 151.4000  
## 8     14 161.8000  
## 9     16 182.0000  
## 10    18 202.9000  
## 11    20 233.8889  
## 12    21 238.5556
```

作出 weight 的均值关于时间的图象

```
plot(weight~Time, data = ChickWeight.diet4.mean, type = "o",
      main = "Mean Weight Against Time")
```



#### 4.4 (d)

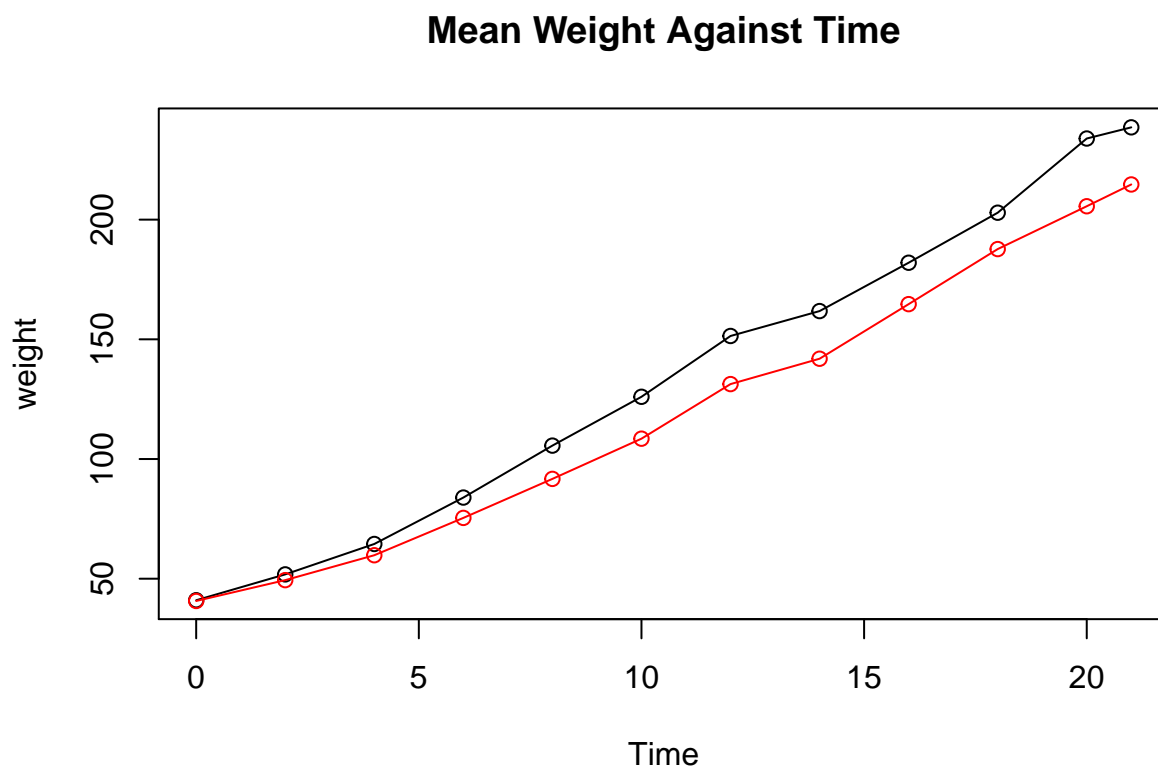
首先提取 group 2 的数据

```
ChickWeight.diet2 <- ChickWeight.split.diet$`2`
ChickWeight.diet2.mean <- with(ChickWeight.diet2,
                                aggregate(weight, by = list(Time), mean))
colnames(ChickWeight.diet2.mean) <- c("Time", "weight")
```

再向图中添加 group 2 的图象

```
plot(weight~Time, data = ChickWeight.diet4.mean, type = "o",
      main = "Mean Weight Against Time")
with(ChickWeight.diet2.mean, points(Time, weight, col = "red", type="o"))
```



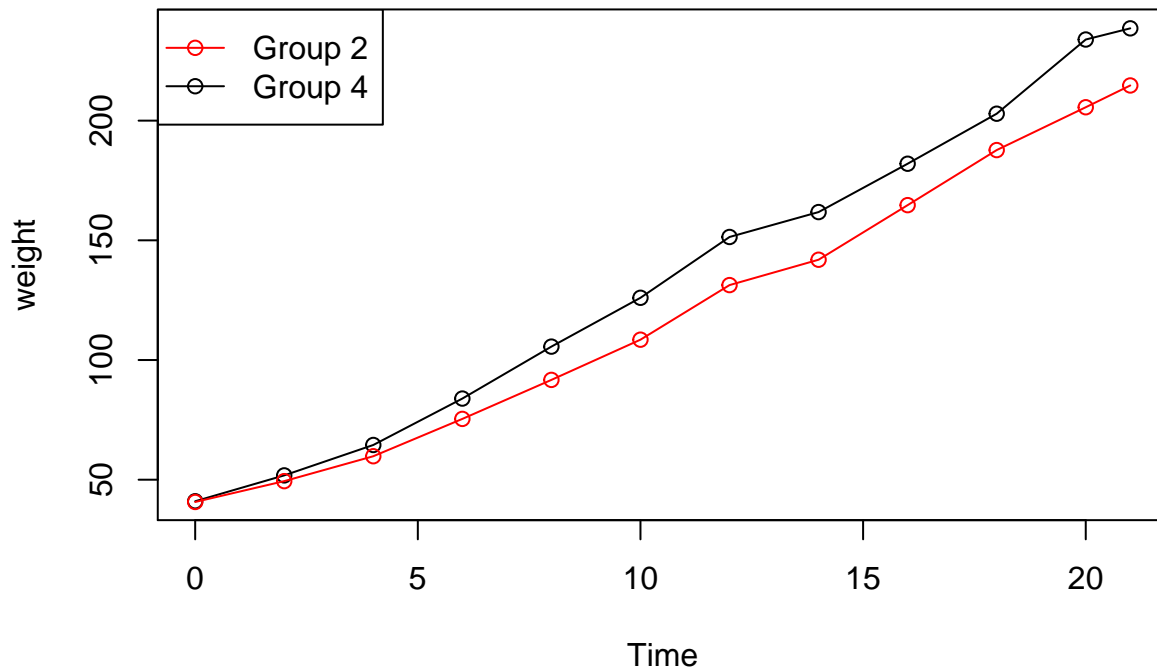


#### 4.5 (e)

在左上角添加 legend，效果如下所示

```
plot(weight~Time, data = ChickWeight.diet4.mean, type = "o",  
      main = "Mean Weight Against Time")  
with(ChickWeight.diet2.mean, points(Time, weight, col = "red", type="o"))  
legend("topleft", c("Group 2", "Group 4"), lty = c(1, 1),  
      pch = c(1, 1), col = c("red", "black"))
```

## Mean Weight Against Time



## 5 十

首先构造数据框

```
time = c(2, 3, 6, 8, 9, 10, 11, 13, 14, 16, 21, 22, 24, 26, 27, 7,
         13, 15, 18, 23, 20, 24, 1, 5, 17, 18, 25, 18, 25, 4, 19)
tumorsize = c(rep("<=3cm", 22), rep(">3cm", 9))
number = c(rep(1, 15), rep(2, 5), 3, 4, rep(1, 5), 2, 2, 3, 4)
df = data.frame(time, tumorsize, number)
```

因 tumorsize 仅取两个值，则将其看成因子然后进行下面的 Poisson 回归

```
model <- glm(number ~ time + factor(tumorsize), data = df, family = "poisson")
```

结果为

```
summary(model)
```

```
##
## Call:
## glm(formula = number ~ time + factor(tumorsize), family = "poisson",
##      data = df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -0.8183 -0.4753 -0.2923 0.3319 1.5446
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.14568    0.34766   0.419   0.675
## time              0.01478    0.01883   0.785   0.433
## factor(tumorsize)>3cm 0.20511    0.30620   0.670   0.503
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 12.800  on 30  degrees of freedom
## Residual deviance: 11.757  on 28  degrees of freedom
## AIC: 88.568
##
## Number of Fisher Scoring iterations: 4
```

可以看出 tumorsize 的系数为 0.20511，在泊松回归中，因变量以条件均值的对数形式  $\ln(\lambda)$  来建模，则 tumorsize 变大，number 的对数均值将增加 0.20511，然而该系数的 p 值为  $0.503 > 0.05$ ，不够显著。

如果不考虑时间，采用下面的 Poisson 回归，

```
model2 <- glm(number ~ factor(tumorsize), data = df, family = "poisson")
```

结果为

```
summary(model2)

##
## Call:
## glm(formula = number ~ factor(tumorsize), family = "poisson",
##      data = df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -0.6363  -0.3996  -0.3996   0.4277   1.7326
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.3747    0.1768   2.120   0.034 *
## factor(tumorsize)>3cm 0.2007    0.3062   0.655   0.512
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 12.80  on 30  degrees of freedom
```

```
## Residual deviance: 12.38  on 29  degrees of freedom
## AIC: 87.191
##
## Number of Fisher Scoring iterations: 4
```

可以看出 tumorsize 的系数为 0.2007，在泊松回归中，因变量以条件均值的对数形式  $\ln(\lambda)$  来建模，则 tumorsize 变大，number 的对数均值将增加 0.2007，然而该系数的 p 值为  $0.512 > 0.05$ ，表明该系数的估计不够显著。