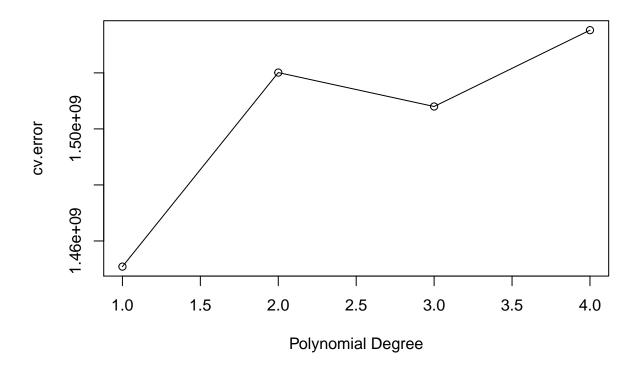
# HW 3

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#### 1. Cross Validation

```
library(boot)
library(MASS)
income <- read.csv("income.txt", sep = "", header = T)</pre>
glm.fit1 = glm(y~x, data=income)
cv.error1=cv.glm(income, glm.fit1, K=5)
glm.fit2 = glm(y-poly(x,2), data=income)
# quadratic model
cv.error2=cv.glm(income, glm.fit2, K=5)
glm.fit3 = glm(y-poly(x,3), data=income)
# cubic model
cv.error3=cv.glm(income, glm.fit3, K=5)
glm.fit4 = glm(y-poly(x,4), data=income)
# quartic model
cv.error4=cv.glm(income, glm.fit4, K=5)
cv.error=c(cv.error1$delta[1],cv.error2$delta[1],cv.error3$delta[1],cv.error4$delta[1])
d=c(1,2,3,4)
plot(d,cv.error, main = "Prediction Error", xlab = "Polynomial Degree")
lines(d,cv.error)
```

### **Prediction Error**

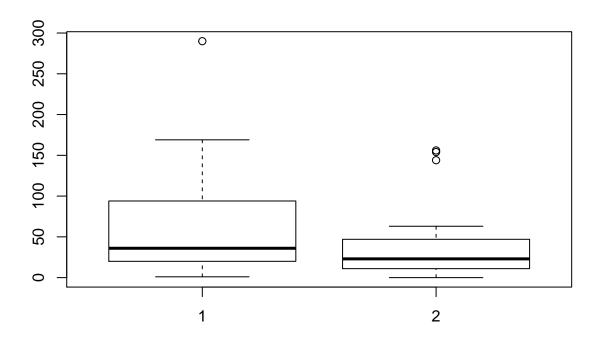


Depending on the situation a degree of either 1 or 4 would be acceptable. A linear model would be much more interpretable, while a polynomial of degree 4 has a smaller prediction error.

## 2 Mann-Whitney Test

We want to test the hypothesis that children exposed to violent TV were slower to react to real-life violence than children who were not exposed to violent TV. The response times were measured in seconds for both groups. First let's examine the data visually:

```
violent <- read.csv("violent.txt", sep = " ")
x <- violent$karate
y <- violent$olympics
boxplot(x,y)</pre>
```



(a)

If we let F be the CDF of violent tv watcher's reaction times, and G be the cdf of reaction times of children not exposed the violent TV, our hypothesis statements would be  $H_0: F(t) = G(t)$  vs  $H_0: F(t) = G(t - \Delta)$  for some  $\Delta < 0$ 

```
##
## Wilcoxon rank sum test
##
## data: x and y
## W = 274, p-value = 0.09222
## alternative hypothesis: true location shift is greater than 0
```

With a U test statistic of 274 and a p-value of .09, would fail to reject the null hypothesis. However, I think that would be a misleading conclusion based on an arbitrarily chosen "significance" level and that a p-value of .09 suggest there is evidence that reaction times were longer for children exposed to violent TV.

To convert our U statistic to the W statistic, we can subtract  $\frac{n(n+1)}{2}$  which in this case is 231 so our W statistic would be 43.

To conduct a hypothesis test based on a large sample approximation, we can set the exact argument to false in the wilcox.test function.

```
wilcox.test(x,y, alternative = "greater", exact = FALSE)
```

```
##
## Wilcoxon rank sum test with continuity correction
##
## data: x and y
## W = 274, p-value = 0.09122
## alternative hypothesis: true location shift is greater than 0
```

And we come to the same conclusion as before with our p-value about .001 lower.

4.

```
x=sort(c(2.1, 1.9, 2.6, 3.3))
y=sort(c(1.9, 2.6, 3.7, NA))
ranky <- c(1.5,4.5,7)

df <- data.frame(x = x, y = c(y, NA), ranky = c(ranky, NA))</pre>
```

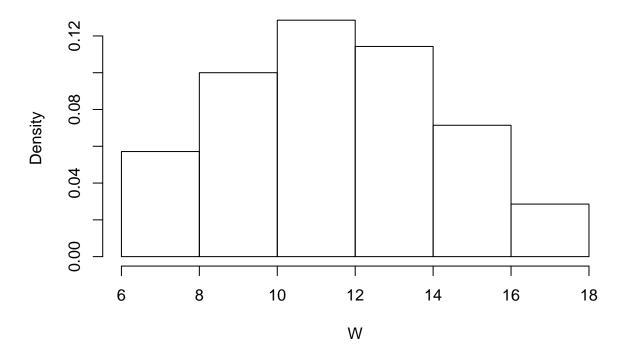
We can find the W statistic by summing the ranks of Y. This gives us a W statistic of 13.

```
x=sort(c(2.1, 1.9, 2.6, 3.3))
#remove NA
y=sort(c(1.9, 2.6, 3.7))

xy <- c(x,y)
ranksums <- colSums(combn(1:7, 3))

hist(ranksums, probability = T, main = "Distribution of W", xlab = "W")</pre>
```

## **Distribution of W**



To find how extreme W is, we can look at a tabled version of the above distribution:

```
table(ranksums)
```

```
## ranksums
## 6 7 8 9 10 11 12 13 14 15 16 17 18
## 1 1 2 3 4 4 5 4 4 3 2 1 1
```

Our p-value would be the number of ways we can get a test statistic as or larger than 13 under the null hypothesis. This would be 15/35 or .43. So we would fail to reject the null hypothesis and have no evidence of a difference in the location of the distributions for X and Y.