# MSMS - 106

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### Practical 04



Fit a binomial distribution to the given dataset.

x	0	1	2	3	4	5	6	7	8
f	5	9	22	29	36	25	10	3	1

Also perform a  $\chi^2$  goodness of fit test.

## **④** Fitting a Binomial Distribution

Here 
$$n = 8$$
.  $\bar{x} = \frac{\sum_{i=1}^{n} x_i f_i}{\sum_{i=1}^{n} f_i}$ ;  $\hat{p} = \frac{\bar{x}}{n}$ .

```
x <- 0:8; n <- length(x)-1
freq <- c(5, 9, 22, 29, 36, 25, 10, 3, 1)
```

```
weighted_mean <- function(x, weight){
    xw <- 0
    w <- 0
    for (i in 1:length(x)) {
        xw <- xw + x[i] * weight[i]
        w <- w + weight[i]
    }
    return(xw / w)
}</pre>
```

```
x_bar <- weighted_mean(x, freq)
x_bar
## [1] 3.557143</pre>
```

 $\bar{x}=3.5571429.$  So  $\hat{p}=0.4446429.$  Now we fit  $Bin(8,\,0.4446429)$  distribution to the given data.

Now 
$$P(X = 0) = (1 - \hat{p})^8 = 0.0090485$$
 and

$$P(X = i + 1) = \frac{n - i}{i + 1} \cdot \frac{p}{1 - p} \cdot P(X = i) \ \forall i = 0, 1, n - 1.$$

Also, expected frequency of  $i = k \cdot P(X = i) \ \forall i = 0 \ (1)n$ , where  $k = \sum_{i=0}^{n} f_i$  is the total frequency.

```
p <- x_bar / n
```

```
probabilities <- c((1 - p)^n)

i <- 1
while (i <= 8) {
  probabilities[i+1] <- ((n-(i-1)) / (i)) * (p / (1-p)) * probabilities[i]

i <- i + 1
}</pre>
```

```
total_frequency <- 0

for (i in 1:length(freq)) {
  total_frequency <- total_frequency + freq[i]
}</pre>
```

```
expected_frequencies <- c()

for (i in 1:9) {
   expected_frequencies[i] <- probabilities[i] * total_frequency
}</pre>
```

Here is our fit.

```
df <- data.frame(x = x,</pre>
                  observed = freq,
                  expected = expected_frequencies)
df
## x observed expected
## 1 0 5 1.2667967
             9 8.1140163
## 2 1
          9 8.1140163
22 22.7375088
## 3 2
## 4 3
            29 36.4092584
            36 36.4385263
## 5 4
## 6 5 25 23.3394033
## 7 6 10 9.3432660
## 8 7 3 2.1373204
## 9 8 1 0.2139038
```

```
sum(df$observed); sum(df$expected)
## [1] 140
## [1] 140
```

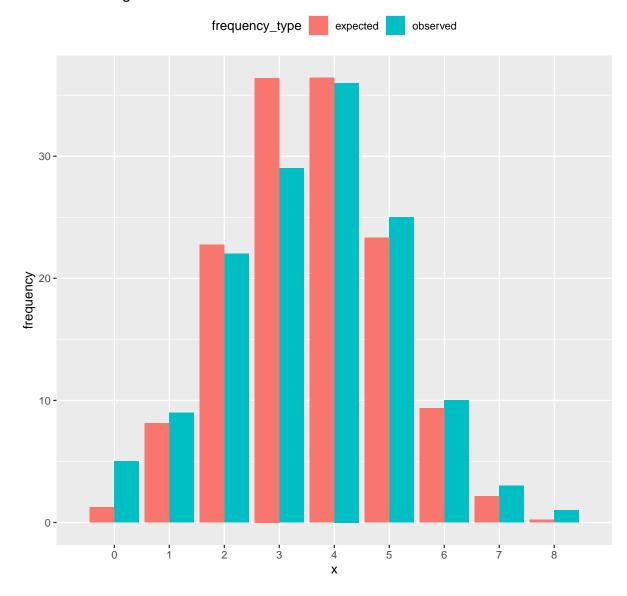
Total expected frequency and total observed frequency are also equal.

A visualization of the fit will be great.

## library(tidyverse)

```
df_melted %>%
  ggplot(aes(x = x, y = frequency, fill = frequency_type)) +
  geom_col(position = "dodge") +
  scale_x_discrete(limits = x) +
  labs(title = "Visualizing the fit") +
  theme(legend.position = "top")
```

## Visualizing the fit



### $\bigcirc$ $\chi^2$ Goodness of fit test

 $\chi^2 = \sum_{i=1}^m \frac{(f_i - kp_i)^2}{kp_i}$  where m is the number of classes,  $f_i$  is the observed frequency of i-th class,

 $p_i$  is the theoretical probability of belonging to *i*-th class, k is total frequency.

In large sample,  $\chi^2 \sim \chi^2_{m-1}$ .

We also must have expected frequency greater than or equal to 5 for each class.

Here, in order to achieve so, we shall combine similar categories x = 0 & 1; x = 6 & 7 & 8.

Now we have

```
new_df
##
          x observed expected
## 1
       0, 1 14 9.380813
## 2
         2
                  22 22.737509
                 29 36.409258
## 3
          3
                  36 36.438526
## 5
                  25 23.339403
## 6 6, 7, 8
               14 11.694490
```

See that each of the expected frequencies is greater than or equal to 5. Number of classes m is 6. Now we perform  $\chi^2$  goodness of fit test.

```
observed_chi_sq <- 0

for (i in 1:dim(new_df)[1]) {
   d <- new_df$observed[i] - new_df$expected[i]
   e <- new_df$expected[i]
   observed_chi_sq <- observed_chi_sq + (d^2) / e
}</pre>
```

```
observed_chi_sq; qchisq(0.05, 5, lower.tail = FALSE)

## [1] 4.384173

## [1] 11.0705
```

Observed  $\chi^2 = 4.3841734 < \chi^2_{0.05,5} = 11.0704977$ . So we fail to reject the null hypothesis of goodness of fit test and conclude that there is not enough evidence to claim that the given data is not from a Binomial population.