1 Basic statistical models

Sample statistic	Distribution feature
Graphical Empirical distribution function F_n Kernel density estimate $f_{n,h}$ and histogram (Number of X_i equal to $a)/n$	Distribution function F Probability density f Probability mass function $p(a)$
Numerical Sample mean \bar{X}_n Sample median $\operatorname{Med}(X_1, X_2, \dots, X_n)$ p th empirical quantile $q_n(p)$ Sample variance S_n^2 Sample standard deviation S_n $\operatorname{MAD}(X_1, X_2, \dots, X_n)$	Expectation μ Median $q_{0.5} = F^{\text{inv}}(0.5)$ $100p\text{th percentile } q_p = F^{\text{inv}}(p)$ Variance σ^2 Standard deviation σ $F^{\text{inv}}(0.75) - F^{\text{inv}}(0.5)$, for symmetric F

Figure 1: Some sample statistics and corresponding distribution features

1.1 The linear regression model

To fit a linear regression model in R, we can use the lm() function, which uses the following syntax:

```
model \leftarrow lm(y \sim x1 + x2, data=df)
```

We can then use the following syntax to use the model to predict a single value:

```
predict(model, newdata = new)
```

The following examples show how to predict a single value using fitted regression models in R.

1.1.1 Simple linear regression model

The following code shows how to fit a simple linear regression model in R:

And we can use the following code to predict the response value for a new observation:

```
#define new observation
new <- data.frame(x = c(5))
# this has to be a dataframe otherwise it will not work.

#use the fitted model to predict the value for the new observation
predict(model, newdata = new)</pre>
```

```
## 1
## 25.36364
```

The model predicts that this new observation will have a response value of 25.36364.

1.1.2 Multiple linear regression model

Multiple Linear Regression Model

The following code shows how to fit a multiple linear regression model in R:

```
#create data df \leftarrow data.frame(x1 = c(3, 4, 4, 5, 5, 6, 7, 8, 11, 12), x2 = c(6, 6, 7, 7, 8, 9, 11, 13, 14, 14), y = c(22, 24, 24, 25, 25, 27, 29, 31, 32, 36))
#fit multiple linear regression model model \leftarrow lm(y \sim x1 + x2, data = df)
```

And we can use the following code to predict the response value for a new observation:

26.17073

The model predicts that this new observation will have a response value of 26.17073.

1.1.3 Plotting a regression model

You can use the R visualization library ggplot2 to plot a fitted linear regression model using the following basic syntax:

```
ggplot(data,aes(x, y)) +
  geom_point() +
  geom_smooth(method='lm')
```

The following example shows how to use this syntax in practice.

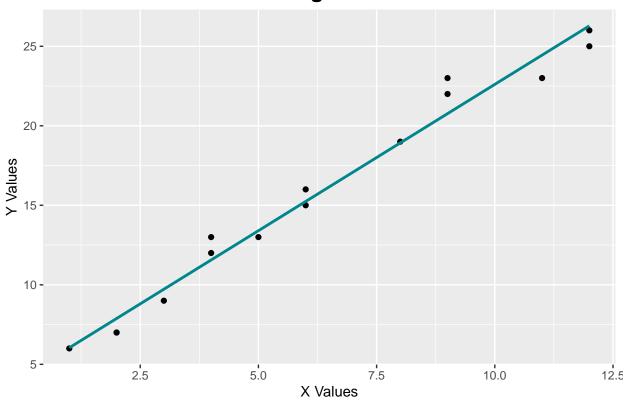
Suppose we fit a simple linear regression model to the following dataset:

```
##
## Call:
## lm(formula = y ~ x, data = data)
##
## Residuals:
## Min    1Q Median   3Q Max
## -1.4444 -0.8013 -0.2426   0.5978   2.2363
##
## Coefficients:
```

```
Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 4.20041
                          0.56730
                                   7.404 5.16e-06 ***
                          0.07857 23.423 5.13e-12 ***
## x
               1.84036
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.091 on 13 degrees of freedom
## Multiple R-squared: 0.9769, Adjusted R-squared: 0.9751
## F-statistic: 548.7 on 1 and 13 DF, p-value: 5.13e-12
# make sure to import the ggplot library: library(ggplot2)
#create plot to visualize fitted linear regression model
ggplot(data, aes(x, y)) +
 geom_point() +
 geom_smooth(method = 'lm', se = FALSE, col = "turquoise4") +
 labs(x = 'X Values', y = 'Y Values', title = 'Linear Regression Plot') +
 #this last line makes the title header bold and in the middle
 theme(plot.title = element_text(hjust = 0.5, size = 16, face = 'bold'))
```

`geom_smooth()` using formula 'y ~ x'

Linear Regression Plot



Note the **se** argument removes the standard error from the visualization of if it is needed simply remove it or set it to TRUE